Colab Link:

https://colab.research.google.com/drive/14wfN6q9cSq-w6vTqYDpSOqfuQAYxn3pD?usp=sharing

#Project Theme: US Company Bankkruptcy Prediction

Team A08: Chih-Hsin (Olivia) Peng, Gaurangi Agrawal, Pei-Hsin (Bonny) Yang, Yu-Chun (Lila) Su

##1. Business Problem

Our analysis involves a thorough examination of numerous feature variables that contain comprehensive information about financial statement indices, from Current Assets to Total Operating Expenses, which are essential in providing an in-depth understanding of a company's financial health. In addition to this, we incorporate the temporal dimension by including a year column, which enables us to unveil trends and conditions over time. Our primary objective is to leverage this extensive dataset to predict a company's financial stability or its likelihood of facing bankruptcy.

##2. Data Source + Variable Description

The dataset we have chosen is from Kaggle, and the company name in the dataset is related to the American public company, which is listed on the New York Stock Exchange and NASDAQ.

Variable Name	Description
company-name	Name of the company
year	Operating years of the company
status_label	Tells us whether the company has declared bankruptcy or not. 1 - Alive/ Not Bankrupt : 0 - Failed/ Bankrupt
X1	Current assets - All the assets of a company that are expected to be sold or used as a result of standard business operations over the next year.
X2	Cost of goods sold - The total amount a company paid as a cost directly related to the sale of products.
X3	Depreciation and amortization - Depreciation refers to the loss of value of a tangible fixed asset over time (such as property, machinery, buildings, and plant). Amortization refers to the loss of value of intangible assets over time.
X4	EBITDA - Earnings before interest, taxes, depreciation, and amortization. It is a measure of a company's overall financial performance, serving as an alternative to net income.
X5	Inventory - The accounting of items and raw materials that a company either uses in production or sells.
X6	Net Income - The overall profitability of a company after all expenses and costs have been deducted from total revenue.
X7	Total Receivables - The balance of money due to a firm for goods or services delivered or used but not yet paid for by

Variable Name	Description
	customers.
X8	Market value - The price of an asset in a marketplace. In this dataset, it refers to the market capitalization since companies are publicly traded in the stock market.
X9	Net sales - The sum of a company's gross sales minus its returns, allowances, and discounts.
X10	Total assets - All the assets, or items of value, a business owns.
X11	Total Long-term debt - A company's loans and other liabilities that will not become due within one year of the balance sheet date.
X12	EBIT - Earnings before interest and taxes.
X13	Gross Profit - The profit a business makes after subtracting all the costs that are related to manufacturing and selling its products or services.
X14	Total Current Liabilities - The sum of accounts payable, accrued liabilities, and taxes such as Bonds payable at the end of the year, salaries, and commissions remaining.
X15	Retained Earnings - The amount of profit a company has left over after paying all its direct costs, indirect costs, income taxes, and its dividends to shareholders.
X16	Total Revenue - The amount of income that a business has made from all sales before subtracting expenses. It may include interest and dividends from investments.
X17	Total Liabilities - The combined debts and obligations that the company owes to outside parties.
X18	Total Operating Expenses - The expenses a business incurs through its normal business operations.

##3. Who cares about this problem & why?

Knowing who is concerned about a particular issue offers different perspectives. Firstly, for a company, understanding its financial health guides its future plans. If a company faces money troubles, it might find ways to earn more, spend less on making things, or seek outside help, like selling company shares or bonds. This understanding helps companies change how they work to stay financially strong.

At the same time, investors focus on how a company's finances affect their investments. They want to put money where they think it'll grow. By looking at a company's past finances, investors can guess if it might close down or not make money. Using this info, they decide where to keep investing and where to pull back. So, knowing a company's financial situation is crucial for both the company itself and the people investing in it. Predicting if a company will do well or not guides the actions of both businesses and investors.

##4. Data Preprocessing

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('/content/american_bankruptcy.csv')

# rename the column's name
df.rename(columns={'status_label' : 'is_bankruptcy','X1': 'Current
assets', 'X2': 'Cost of goods sold', 'X3': 'Depreciation and
amortization', 'X4': 'EBITDA', 'X5': 'Inventory','X6': 'Net Income',
'X7': 'Total Receivables', 'X8': 'Market Value', 'X9': 'Net Sales',
'X10': 'Total Assets','X11': 'Total Long-term Debt', 'X12': 'EBIT',
'X13': 'Gross Profit', 'X14': 'Total Current Liabilities', 'X15':
'Retained Earnings', 'X16': 'Total Revenue', 'X17': 'Total
Liabilities', 'X18': 'Total Operating Expenses'},inplace=True)

# set 'company_name' and 'year' as duel index
df.set_index(['company_name', 'year'],inplace=True)

# change 'is_bankruptcy' column into 0 = failed / 1 = alive
# set(df['status_label']) == {'alive', 'failed'}
mapping = {'alive':0, 'failed':1}
df['is_bankruptcy'] = df['is_bankruptcy'].replace(mapping)
```

##**5. Feature Selection**

```
# pre-processing the train/ test dataset, handling the missing value,
and standardize the variables
X = df.drop('is_bankruptcy',axis=1)
y = df['is_bankruptcy']

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.25,random_state=42)


# dealing with null value before using ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

numeric_pipeline =
Pipeline([('imputer',SimpleImputer(strategy='mean')),
('scaler',StandardScaler())])
```

```
                               # after handling the missing value,
standardize the numerical variables

from sklearn.compose import ColumnTransformer
numerical_variable = ['Current assets', 'Cost of goods sold',
       'Depreciation and amortization', 'EBITDA', 'Inventory', 'Net
Income',
       'Total Receivables', 'Market Value', 'Net Sales', 'Total
Assets',
       'Total Long-term Debt', 'EBIT', 'Gross Profit',
       'Total Current Liabilities', 'Retained Earnings', 'Total
Revenue',
       'Total Liabilities', 'Total Operating Expenses']

transformer =
ColumnTransformer([('numerical_variable',numeric_pipeline,numerical_va
riable)])
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
pipeline = Pipeline([('transformer',transformer),
('LogisticRegression',LogisticRegression(random_state=42))])
pipelineX = df.drop('is_bankruptcy',axis=1)
y = df['is_bankruptcy']

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.25,random_state=42)


# dealing with null value before using ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

numeric_pipeline =
Pipeline([('imputer',SimpleImputer(strategy='mean')),
('scaler',StandardScaler())])
                               # after handling the missing value,
standardize the numerical variables

from sklearn.compose import ColumnTransformer
numerical_variable = ['Current assets', 'Cost of goods sold',
       'Depreciation and amortization', 'EBITDA', 'Inventory', 'Net
Income',
       'Total Receivables', 'Market Value', 'Net Sales', 'Total
Assets',
       'Total Long-term Debt', 'EBIT', 'Gross Profit',
       'Total Current Liabilities', 'Retained Earnings', 'Total
Revenue',
       'Total Liabilities', 'Total Operating Expenses']
```

```
transformer =
ColumnTransformer([('numerical_variable',numeric_pipeline,numerical_va
riable)])
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
pipeline = Pipeline([('transformer',transformer),
('LogisticRegression',LogisticRegression(random_state=42))])
pipeline
```

```
Pipeline(steps=[('transformer',

ColumnTransformer(transformers=[('numerical_variable',

Pipeline(steps=[('imputer',

SimpleImputer()),

('scaler',

StandardScaler())]),
                                                  ['Current assets',
                                                   'Cost of goods
sold',
                                                   'Depreciation and '
                                                   'amortization',
                                                   'EBITDA',
'Inventory',
                                                   'Net Income',
                                                   'Total
Receivables',
                                                   'Market Value',
'Net Sales',
                                                   'Total Assets',
                                                   'Total Long-term
Debt',
                                                   'EBIT', 'Gross
Profit',
                                                   'Total Current
Liabilities',
                                                   'Retained
Earnings',
                                                   'Total Revenue',
                                                   'Total
Liabilities',
                                                   'Total Operating '
                                                   'Expenses'])])),
                ('LogisticRegression',
LogisticRegression(random_state=42))])
```

###5.1 Select KBest

```
# step 1: use SelectKBest to pick the best features
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif # because I get
numerical input and a categorical target variable, so choose f_classif
to make the calculation
best_k_select = SelectKBest(score_func=f_classif)

# step 2: re-define the pipeline you want to put in GridSearchCV
best_k_select_pipeline = Pipeline([('transformer',transformer),
('select',best_k_select),
('LogisticRegression',LogisticRegression(random_state=42))])

# step 3: use gridsearch to find the best features
from sklearn.model_selection import GridSearchCV
param_grid = {'select__k': range(1, X_train.shape[1] + 1)}
grid_search = GridSearchCV(estimator=best_k_select_pipeline,
param_grid=param_grid,cv=5, scoring='balanced_accuracy')
grid_search.fit(X_train,y_train)

# step 4: after fitting, show the result
# 4-1
result = pd.DataFrame(grid_search.cv_results_)
#display(grid_search_all_result)
result = result.sort_values(by='mean_test_score',ascending=False)
display(result.filter(regex= '(^param_|mean_test_score)', axis=1))
                    # regular expression
                             # ^ : start from
                             # | : or
# 4-2
final_pick = grid_search.best_estimator_
print('The selected features are=\n',
final_pick["transformer"].get_feature_names_out()
[final_pick["select"].get_support()])
```

	param_select__k	mean_test_score
17	18	0.503538
16	17	0.502628
15	16	0.502628
14	15	0.501163
13	14	0.501163
12	13	0.501163
11	12	0.500528
9	10	0.500334
10	11	0.500187
6	7	0.499957
2	3	0.499955
7	8	0.499947
5	6	0.499947

```
1                2          0.499946
8                9          0.499938
0                1          0.499927
3                4          0.499909
4                5          0.499900

The selected features are=
 ['numerical_variable__Current assets'
 'numerical_variable__Cost of goods sold'
 'numerical_variable__Depreciation and amortization'
 'numerical_variable__EBITDA' 'numerical_variable__Inventory'
 'numerical_variable__Net Income' 'numerical_variable__Total
Receivables'
 'numerical_variable__Market Value' 'numerical_variable__Net Sales'
 'numerical_variable__Total Assets'
 'numerical_variable__Total Long-term Debt' 'numerical_variable__EBIT'
 'numerical_variable__Gross Profit'
 'numerical_variable__Total Current Liabilities'
 'numerical_variable__Retained Earnings'
 'numerical_variable__Total Revenue'
 'numerical_variable__Total Liabilities'
 'numerical_variable__Total Operating Expenses']
```

###**5.2 Select From Model**

```
# step 1: decide use SelectFromModel to select the best features, and
decide to use Lasso model
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import Lasso
select_from_model = SelectFromModel(Lasso())

# step 2: re-define the pipeline, so you can put in GridSearchCV
select_from_model_pipeline = Pipeline([('transformer',transformer),
('select',select_from_model),
('LogisticRegression',LogisticRegression(random_state=42))])

# step 3: use gridsearch to find the best features
from sklearn.model_selection import GridSearchCV
param_grid = {'select__estimator__alpha': [10, 100,
1000],'select__threshold': ['mean', 'median']}
grid_search =
GridSearchCV(estimator=select_from_model_pipeline,param_grid =
param_grid, cv=5, scoring='balanced_accuracy')
grid_search.fit(X_train, y_train)

# step 4: after fitting, show the result
# 4-1
result = pd.DataFrame(grid_search.cv_results_)
result = result.sort_values(by="mean_test_score", ascending=False)
```

```
display(result.filter(regex='(^param_|mean_test_score)', axis=1))
# 4-2
final_pick = grid_search.best_estimator_
print('The selected features are=\n',
final_pick["transformer"].get_feature_names_out()
[final_pick["select"].get_support()])
```

```
  param_select__estimator__alpha param_select__threshold
mean_test_score
0                             10                    mean
0.503538
1                             10                  median
0.503538
2                            100                    mean
0.503538
3                            100                  median
0.503538
4                           1000                    mean
0.503538
5                           1000                  median
0.503538

The selected features are=
 ['numerical_variable__Current assets'
 'numerical_variable__Cost of goods sold'
 'numerical_variable__Depreciation and amortization'
 'numerical_variable__EBITDA' 'numerical_variable__Inventory'
 'numerical_variable__Net Income' 'numerical_variable__Total
Receivables'
 'numerical_variable__Market Value' 'numerical_variable__Net Sales'
 'numerical_variable__Total Assets'
 'numerical_variable__Total Long-term Debt' 'numerical_variable__EBIT'
 'numerical_variable__Gross Profit'
 'numerical_variable__Total Current Liabilities'
 'numerical_variable__Retained Earnings'
 'numerical_variable__Total Revenue'
 'numerical_variable__Total Liabilities'
 'numerical_variable__Total Operating Expenses']
```

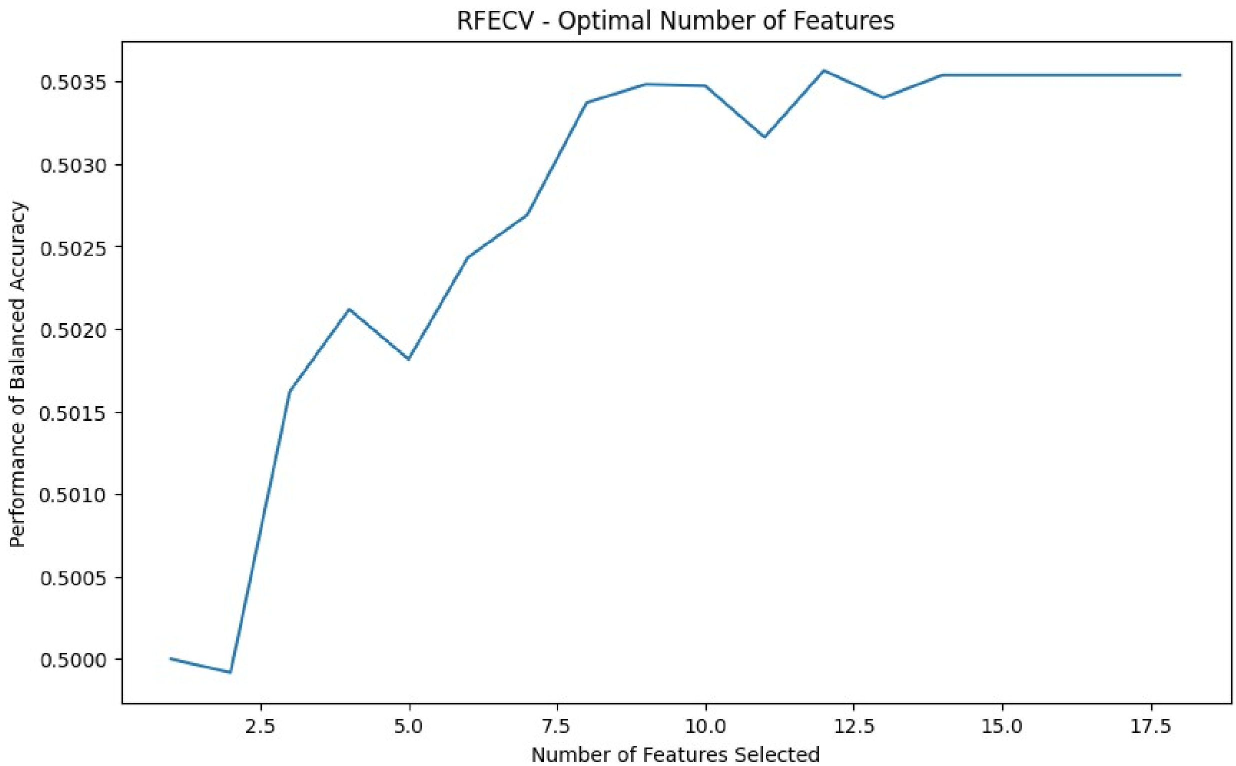
###**5.3 Recursive Feature Elimination**

```
# step 1: decide to use RFECV to select the best features
from sklearn.feature_selection import RFECV
rfecv = RFECV(LogisticRegression(random_state=42),
scoring='balanced_accuracy')

# step 2: re-define the pipeline, add 'select' in to the previous
pipeline
rfecv_pipeline = Pipeline([('transformer',transformer),
```

```python
('select',rfecv),
('LogisticRegression',LogisticRegression(random_state=42))])
rfecv_pipeline.fit(X_train, y_train)

# step 3: show the result
print('Optimal number of features',rfecv.n_features_)
# .n_features_: attributes of rfecv, shows the number of selected
features after the recursive feature elimination process
print('The selected features are=\n',
rfecv_pipeline['transformer'].get_feature_names_out()[rfecv.support_])
```

```
Optimal number of features 12
The selected features are=
 ['numerical_variable__Current assets' 'numerical_variable__EBITDA'
 'numerical_variable__Inventory' 'numerical_variable__Net Income'
 'numerical_variable__Total Receivables'
 'numerical_variable__Market Value'
 'numerical_variable__Total Long-term Debt' 'numerical_variable__EBIT'
 'numerical_variable__Gross Profit'
 'numerical_variable__Total Current Liabilities'
 'numerical_variable__Retained Earnings'
 'numerical_variable__Total Liabilities']
```

```python
# step 4: plot
plt.figure(figsize=(10, 6))
plt.title("RFECV - Optimal Number of Features")
plt.xlabel("Number of Features Selected")
plt.ylabel("Performance of Balanced Accuracy")
mean_test_score = rfecv.cv_results_['mean_test_score']
plt.plot(range(1, len(mean_test_score ) + 1), mean_test_score);
```



###5.4 Sequential Feature Selection: Forward and Backward

```
# default: forward
from mlxtend.feature_selection import SequentialFeatureSelector
sfs = SequentialFeatureSelector(LogisticRegression(random_state=42),
k_features="best", scoring='balanced_accuracy',forward=True)

sfs_pipeline = Pipeline([('transformer',transformer),('select',sfs),
('LogisticRegression',LogisticRegression(random_state=42))])
sfs_pipeline.fit(X_train, y_train)

all_result = pd.DataFrame.from_dict(sfs.get_metric_dict()).T
display(all_result.sort_values(by='avg_score',ascending=False))
```

```
                                               feature_idx  \
17  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
16  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
15  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
14    (0, 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 16)
13       (0, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 16)
18  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
9                   (4, 5, 6, 7, 9, 10, 11, 12, 16)
11            (2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 16)
10               (2, 4, 5, 6, 7, 9, 10, 11, 12, 16)
8                      (4, 6, 7, 9, 10, 11, 12, 16)
12         (0, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 16)
```

```
7                               (4, 6, 7, 9, 10, 11, 16)
6                                  (6, 7, 9, 10, 11, 16)
5                                     (6, 9, 10, 11, 16)
4                                        (9, 10, 11, 16)
3                                            (9, 11, 16)
2                                               (11, 16)
1                                                  (11,)

                                            cv_scores avg_score  \
17  [0.5043231150613701, 0.5038300988665965, 0.503...  0.503685
16  [0.5043231150613701, 0.5038300988665965, 0.503...  0.503685
15  [0.5043231150613701, 0.5038300988665965, 0.503...  0.503685
14  [0.5043231150613701, 0.5038300988665965, 0.503...  0.503685
13  [0.5043231150613701, 0.5038300988665965, 0.503...  0.503685
18  [0.5035889196963023, 0.5038300988665965, 0.503...  0.503538
9   [0.5043231150613701, 0.5032311163304729, 0.502...  0.503299
11  [0.5043231150613701, 0.5032311163304729, 0.502...  0.503299
10  [0.5043231150613701, 0.5032311163304729, 0.502...  0.503299
8   [0.5043684624221537, 0.5033671584128236, 0.502...  0.503224
12  [0.5036796144178695, 0.5032311163304729, 0.503...  0.503179
7   [0.5037249617786531, 0.5034125057736073, 0.501...  0.502994
6   [0.5036796144178695, 0.5027681758767001, 0.501...  0.502847
5   [0.5029454190528017, 0.5027681758767001, 0.501...  0.502304
4   [0.5023926131308681, 0.5022145407013601, 0.501...  0.501834
3   [0.5005074585611499, 0.5004175930929893, 0.501...  0.500684
2   [0.4998186105568656, 0.5002815510106384, 0.501...  0.500334
1   [0.4998639579176492, 0.499773263196082, 0.5005...  0.500029

                                        feature_names  ci_bound
std_dev  \
17  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000553
0.00043
16  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000553
0.00043
15  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000553
0.00043
14    (0, 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 16)  0.000553
0.00043
13       (0, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 16)  0.000553
0.00043
18  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000333
0.000259
9                        (4, 5, 6, 7, 9, 10, 11, 12, 16)  0.000886
0.000689
11                 (2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 16)  0.000886
0.000689
10                    (2, 4, 5, 6, 7, 9, 10, 11, 12, 16)  0.000886
0.000689
8                           (4, 6, 7, 9, 10, 11, 12, 16)  0.000861
```

```
0.00067
12          (0, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 16)  0.000642
0.0005
7                          (4, 6, 7, 9, 10, 11, 16)  0.000864
0.000673
6                             (6, 7, 9, 10, 11, 16)  0.000829
0.000645
5                                (6, 9, 10, 11, 16)  0.000988
0.000768
4                                   (9, 10, 11, 16)  0.000548
0.000426
3                                       (9, 11, 16)  0.000739
0.000575
2                                          (11, 16)  0.000586
0.000456
1                                             (11,)  0.000352
0.000274

     std_err
17  0.000215
16  0.000215
15  0.000215
14  0.000215
13  0.000215
18   0.00013
9   0.000345
11  0.000345
10  0.000345
8   0.000335
12   0.00025
7   0.000336
6   0.000322
5   0.000384
4   0.000213
3   0.000287
2   0.000228
1   0.000137
```

```python
# back
from mlxtend.feature_selection import SequentialFeatureSelector
sbs = SequentialFeatureSelector(LogisticRegression(random_state=42),
k_features="best", scoring='balanced_accuracy',forward=False)

sbs_pipeline = Pipeline([('transformer',transformer),('select',sbs),
('LogisticRegression',LogisticRegression(random_state=42))])
sbs_pipeline.fit(X_train, y_train)

all_result = pd.DataFrame.from_dict(sbs.get_metric_dict()).T
display(all_result.sort_values(by='avg_score',ascending=False))
```

```
                                         feature_idx  \
9                        (0, 3, 4, 6, 7, 10, 12, 13, 16)
16  (0, 1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 15...
15  (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 15, 1...
14   (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 16, 17)
13       (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 16)
17  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
10                    (0, 3, 4, 6, 7, 9, 10, 12, 13, 16)
11                (0, 3, 4, 6, 7, 9, 10, 11, 12, 13, 16)
12             (0, 2, 3, 4, 6, 7, 9, 10, 11, 12, 13, 16)
18  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
8                            (0, 3, 4, 6, 7, 10, 13, 16)
7                               (0, 3, 4, 7, 10, 13, 16)
6                                  (0, 3, 7, 10, 13, 16)
5                                      (0, 3, 7, 10, 16)
4                                          (0, 3, 7, 16)
3                                             (0, 7, 16)
1                                                   (0,)
2                                                (0, 16)

                                           cv_scores avg_score  \
9   [0.5042777677005865, 0.5047918602889889, 0.502...  0.503785
16  [0.5049212683440871, 0.5040114883097309, 0.503...  0.503731
15  [0.5049212683440871, 0.5040114883097309, 0.503...  0.503731
14  [0.5049212683440871, 0.5040114883097309, 0.503...  0.503731
13  [0.5049212683440871, 0.5040114883097309, 0.503...  0.503731
17  [0.504323115061370l, 0.5038300988665965, 0.503...  0.503685
10  [0.5042777677005865, 0.5041475303920817, 0.502...  0.503665
11  [0.5042777677005865, 0.5040114883097309, 0.503...  0.503629
12  [0.5042777677005865, 0.5040114883097309, 0.503...  0.503611
18  [0.5035889196963023, 0.5038300988665965, 0.503...  0.503538
8   [0.5042777677005865, 0.5047011655674217, 0.502...  0.503491
7   [0.5036796144178695, 0.5041475303920817, 0.502...  0.503261
6   [0.5030361137743689, 0.5023052354229273, 0.502...  0.502764
5   [0.5030814611351524, 0.5023052354229273, 0.501...  0.502377
4   [0.5011056118438669, 0.5030856074021853, 0.501...  0.502102
3   [0.5005074585611499, 0.5024412775052781, 0.501...  0.501503
1                          [0.5, 0.5, 0.5, 0.5, 0.5]       0.5
2             [0.5, 0.5, 0.5, 0.5, 0.4999546526392164]  0.499991

                                       feature_names  ci_bound
std_dev  \
9                        (0, 3, 4, 6, 7, 10, 12, 13, 16)  0.001068
0.000831
16  (0, 1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 15...  0.001066
0.00083
15  (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 15, 1...  0.001066
0.00083
14   (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 16, 17)  0.001066
0.00083
```

```
13        (0, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 16)  0.001066
0.00083
17  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000553
0.00043
10                  (0, 3, 4, 6, 7, 9, 10, 12, 13, 16)  0.000884
0.000688
11              (0, 3, 4, 6, 7, 9, 10, 11, 12, 13, 16)  0.000838
0.000652
12           (0, 2, 3, 4, 6, 7, 9, 10, 11, 12, 13, 16)   0.00086
0.000669
18  (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...  0.000333
0.000259
8                          (0, 3, 4, 6, 7, 10, 13, 16)  0.001245
0.000968
7                             (0, 3, 4, 7, 10, 13, 16)  0.000963
0.000749
6                                (0, 3, 7, 10, 13, 16)  0.000682
0.00053
5                                    (0, 3, 7, 10, 16)  0.000527
0.00041
4                                        (0, 3, 7, 16)  0.001105
0.000859
3                                           (0, 7, 16)  0.000863
0.000672
1                                                 (0,)       0.0
0.0
2                                              (0, 16)  0.000023
0.000018

     std_err
9   0.000415
16  0.000415
15  0.000415
14  0.000415
13  0.000415
17  0.000215
10  0.000344
11  0.000326
12  0.000335
18   0.00013
8   0.000484
7   0.000375
6   0.000265
5   0.000205
4    0.00043
3   0.000336
1        0.0
2   0.000009
```

In this project, although we considered models like KNN and Random Forest for training, our final choice for feature selection was logistic regression. Logistic regression was preferred for its simplicity, computational efficiency, interpretability, and its suitability for binary classification.

The process involved employing various methods for feature selection. SelectKBest recommended including all 18 features. SelectFromModel, using L1 regularization, also suggested including all features. Recursive feature elimination proposed retaining 12 features. Additionally, forward and backward sequential feature selection advised including 17 and 9 features, respectively. Surprisingly, most methods recommended retaining all features despite different approaches.

##**6. Dataset Exploration**

###**Some Interesting Descriptive Analyses**

We initiated our examination of the dataset, noting its emphasis on financial statements—spanning from Current Assets to Total Operating Expenses. This aligns well with our analysis objectives, leveraging the readily available and crucial financial data for a comprehensive understanding of a company's financial health. This is also the reason why the correlation bewteen each variables is relatively high, as shown in correlation matrix. The inclusion of a year column allows us to uncover trends and conditions over time. If a company declared bankruptcy the previous year, it does not appear in the subsequent year.

Moving on to basic statistical analysis, we find the significantly larger number of alive companies compared to those declaring bankruptcy. This presents a notable challenge, which we will delve into in more detail in our subsequent analyses. We can also observe there is a substantial difference between alive companies and failed companies.

```python
# show some basic information about the dataset
print('top 5 row of the dataset:')
display(df.head(5))
print()
print('info about the dataset:')
display(df.info())
print()
print('check if there are any NULL value in the dataset:')
display(df.isna().sum())
print()
print('basic statistics about the dataset (include = "number"):')
display(df.describe(include = 'number'))
print()
```

```
top 5 row of the dataset:

                       is_bankruptcy  Current assets  Cost of goods
sold  \
company_name year

C_1          1999                  0         511.267            833.107

             2000                  0         485.856            713.811
```

```
                 2001                0         436.656               526.477

                 2002                0         396.412               496.747

                 2003                0         432.204               523.302


                       Depreciation and amortization  EBITDA  Inventory  \
company_name year
C_1          1999                             18.373  89.031    336.018
             2000                             18.577  64.367    320.590
             2001                             22.496  27.207    286.588
             2002                             27.172  30.745    259.954
             2003                             26.680  47.491    247.245

                       Net Income  Total Receivables  Market Value  Net
Sales  \
company_name year

C_1          1999      35.163            128.348      372.7519
1024.333
             2000      18.531            115.187      377.1180
874.255
             2001     -58.939             77.528      364.5928
638.721
             2002     -12.410             66.322      143.3295
606.337
             2003       3.504            104.661      308.9071
651.958

                       Total Assets  Total Long-term Debt    EBIT  Gross
Profit  \
company_name year

C_1          1999       740.998               180.447  70.658
191.226
             2000       701.854               179.987  45.790
160.444
             2001       710.199               217.699   4.711
112.244
             2002       686.621               164.658   3.573
109.590
             2003       709.292               248.666  20.811
128.656

                       Total Current Liabilities  Retained Earnings  \
company_name year
C_1          1999                        163.816            201.026
             2000                        125.392            204.065
```

```
             2001                        150.464            139.603
             2002                        203.575            124.106
             2003                        131.261            131.884

                   Total Revenue  Total Liabilities  Total Operating 
Expenses
company_name year                                                    

C_1          1999       1024.333            401.483                  
935.302
             2000        874.255            361.642                  
809.888
             2001        638.721            399.964                  
611.514
             2002        606.337            391.633                  
575.592
             2003        651.958            407.608                  
604.467


info about the dataset:
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 78682 entries, ('C_1', 1999) to ('C_8971', 2018)
Data columns (total 19 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   is_bankruptcy                  78682 non-null  int64  
 1   Current assets                 78682 non-null  float64
 2   Cost of goods sold             78682 non-null  float64
 3   Depreciation and amortization  78682 non-null  float64
 4   EBITDA                         78682 non-null  float64
 5   Inventory                      78682 non-null  float64
 6   Net Income                     78682 non-null  float64
 7   Total Receivables              78682 non-null  float64
 8   Market Value                   78682 non-null  float64
 9   Net Sales                      78682 non-null  float64
 10  Total Assets                   78682 non-null  float64
 11  Total Long-term Debt           78682 non-null  float64
 12  EBIT                           78682 non-null  float64
 13  Gross Profit                   78682 non-null  float64
 14  Total Current Liabilities      78682 non-null  float64
 15  Retained Earnings              78682 non-null  float64
 16  Total Revenue                  78682 non-null  float64
 17  Total Liabilities              78682 non-null  float64
 18  Total Operating Expenses       78682 non-null  float64
dtypes: float64(18), int64(1)
memory usage: 12.0+ MB

None
```

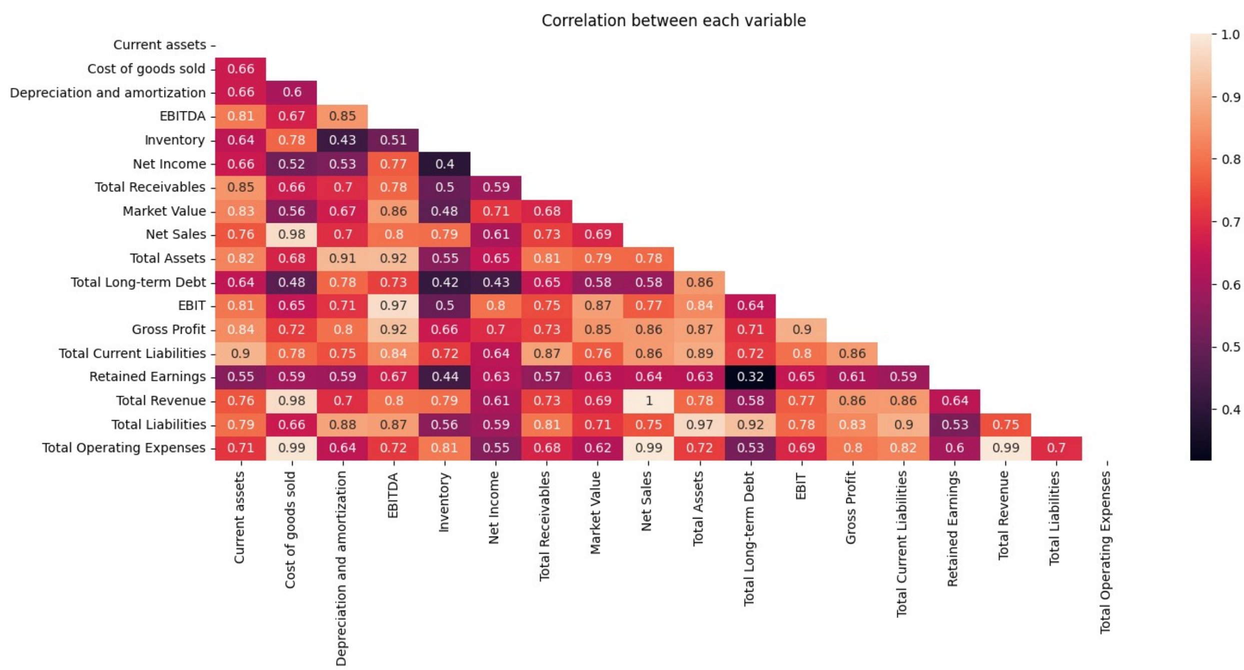
```
check if there are any NULL value in the dataset:

is_bankruptcy                      0
Current assets                     0
Cost of goods sold                 0
Depreciation and amortization      0
EBITDA                             0
Inventory                          0
Net Income                         0
Total Receivables                  0
Market Value                       0
Net Sales                          0
Total Assets                       0
Total Long-term Debt               0
EBIT                               0
Gross Profit                       0
Total Current Liabilities          0
Retained Earnings                  0
Total Revenue                      0
Total Liabilities                  0
Total Operating Expenses           0
dtype: int64


basic statistics about the dataset (include = "number"):

       is_bankruptcy  Current assets  Cost of goods sold  \
count   78682.000000    78682.000000        78682.000000
mean        0.066343      880.362485         1594.529029
std         0.248882     3928.564794         8930.484664
min         0.000000       -7.760000         -366.645000
25%         0.000000       18.924000           17.038250
50%         0.000000      100.449500          103.661000
75%         0.000000      431.526750          634.548000
max         1.000000   169662.000000       374623.000000

       Depreciation and amortization        EBITDA     Inventory  \
count                   78682.000000  78682.000000  78682.000000
mean                      121.234256    376.759424    201.605717
std                       652.376804   2012.023142   1060.766096
min                         0.000000 -21913.000000      0.000000
25%                         1.192000     -0.811000      0.000000
50%                         7.929500     15.034500      7.023000
75%                        47.971750    139.655250     74.747250
max                     28430.000000  81730.000000  62567.000000

          Net Income  Total Receivables  Market Value      Net
Sales  \
count   78682.000000       78682.000000  7.868200e+04   78682.000000
```

```
mean      129.382453          286.832743  3.414355e+03    2364.019706
std      1265.532022         1335.978571  1.841410e+04   11950.068842
min    -98696.000000           -0.006000  1.000000e-04   -1964.999000
25%        -7.415750            3.281250  3.498000e+01      27.548500
50%         1.616000           22.820000  2.275118e+02     186.598500
75%        40.144250          131.580500  1.244890e+03    1046.402500
max    104821.000000        65812.000000  1.073391e+06  511729.000000

        Total Assets  Total Long-term Debt          EBIT   Gross
Profit  \
count   78682.000000          78682.000000  78682.000000
78682.000000
mean     2867.110620            722.483710    255.525035
769.490783
std     12917.944421           3242.170946   1494.643534
3774.703114
min         0.001000             -0.023000 -25913.000000  -
21536.000000
25%        37.363500              0.000000     -2.787000
8.521250
50%       213.203500              7.593500      6.518000
63.581500
75%      1171.364750            248.760750     87.599000
344.074250
max    531864.000000         166250.000000  71230.000000
137106.000000

       Total Current Liabilities  Retained Earnings  Total Revenue  \
count               78682.000000       78682.000000   78682.000000
mean                  610.072255         532.467069    2364.019706
std                  2938.387443        6369.159440   11950.068842
min                     0.001000     -102362.000000   -1964.999000
25%                     8.889250         -68.282750      27.548500
50%                    43.333000          -1.131000     186.598500
75%                   222.817000         146.070000    1046.402500
max                116866.000000      402089.000000  511729.000000

       Total Liabilities  Total Operating Expenses
count       78682.000000              78682.000000
mean         1773.563963               1987.260307
std          8053.684902              10419.629038
min             0.001000               -317.197000
```

```
25%         13.486000          32.872500
50%         81.988000         168.912000
75%        629.975000         875.522250
max     337980.000000      481580.000000
```

```python
# find the correlation between each numerical variables: shows in
heatmap
df_correlation = df.drop(['is_bankruptcy'],axis=1)

plt.figure(figsize=(16,6))
mask = np.triu(np.ones_like(df_correlation.corr(), dtype=bool))
heatmap =
sns.heatmap(df_correlation.corr(),mask=mask,annot=True,cbar=True)
heatmap.set_title("Correlation between each variable",
fontdict={'fontsize': 12})
```

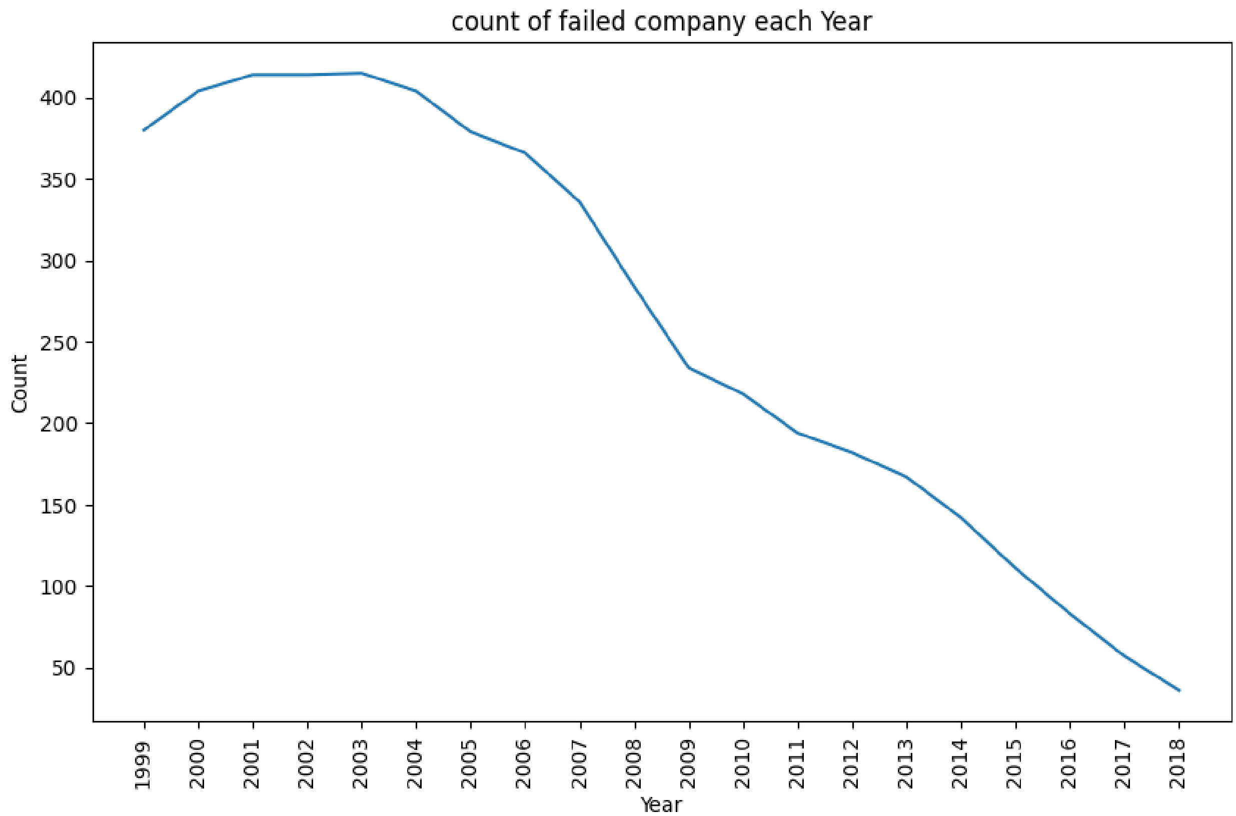
```
Text(0.5, 1.0, 'Correlation between each variable')
```




```python
alivedf = df[df['is_bankruptcy']==0]
faileddf = df[df['is_bankruptcy']==1]

year_counts = faileddf.groupby(level='year').size()
print(year_counts)

plt.figure(figsize=(10, 6))
year_counts.plot(kind='line', xlabel='Year', ylabel='Count',
title='count of failed company each Year')
```

```
plt.xticks(year_counts.index,rotation=90)
plt.show()
```

```
year
1999    380
2000    404
2001    414
2002    414
2003    415
2004    404
2005    379
2006    366
2007    336
2008    284
2009    234
2010    218
2011    194
2012    182
2013    167
2014    142
2015    111
2016     83
2017     57
2018     36
dtype: int64
```




```
print('basic statistics about the alive company dataset (include =
"number"):')
display(alivedf.describe(include = 'number'))
print('basic statistics about the failed company dataset (include =
"number"):')
display(faileddf.describe(include = 'number'))
```

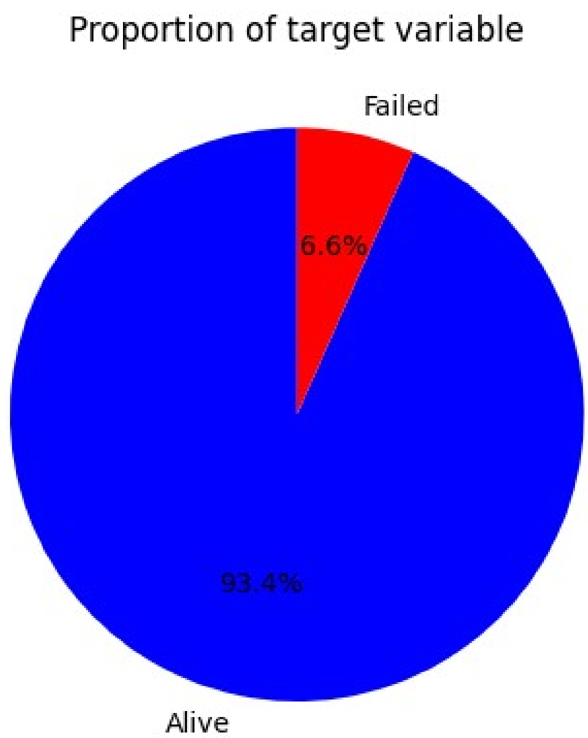
```
basic statistics about the alive company dataset (include = "number"):

       is_bankruptcy  Current assets  Cost of goods sold  \
count        73462.0    73462.000000        73462.000000
mean             0.0      914.542615         1646.982563
std              0.0     4052.047889         9210.587641
min              0.0       -7.760000         -366.645000
25%              0.0       19.235250           17.013500
50%              0.0      102.917500          103.534000
75%              0.0      450.041750          652.468750
max              0.0   169662.000000       374623.000000

       Depreciation and amortization        EBITDA      Inventory  \
count                   73462.000000  73462.000000   73462.000000
mean                      123.746364    393.684586     208.560102
std                       671.282060   2076.601504    1089.918086
min                         0.000000 -21913.000000       0.000000
25%                         1.185250     -0.658000       0.000000
```

```
50%                           7.935000     15.618000     7.117000
75%                          48.001750    144.679000    76.787750
max                       28430.000000  81730.000000  62567.000000

          Net Income  Total Receivables  Market Value      Net
Sales  \
count   73462.000000       73462.000000  7.346200e+04   73462.000000

mean      141.994726         297.794547  3.596015e+03    2447.871581

std      1299.259556        1377.396592  1.902253e+04   12326.442146

min    -98696.000000          -0.006000  1.000000e-04   -1964.999000

25%        -6.484750           3.373000  3.590370e+01      27.748000

50%         2.071500          23.454000  2.408953e+02     187.070000

75%        43.444000         136.101500  1.324400e+03    1083.655000

max    104821.000000       65812.000000  1.073391e+06  511729.000000


        Total Assets  Total Long-term Debt          EBIT   Gross
Profit  \
count   73462.000000          73462.000000  73462.000000
73462.000000
mean     2952.555391            730.516984    269.938080
800.889131
std     13290.496814           3309.223955   1542.468732
3896.084871
min         0.001000             -0.023000 -25913.000000  -
21536.000000
25%        37.736750              0.000000     -2.421750
8.807250
50%       215.006000              7.092500      7.181000
64.823000
75%      1198.552000            245.000000     92.542000
356.430750
max    531864.000000         166250.000000  71230.000000
137106.000000

       Total Current Liabilities  Retained Earnings  Total Revenue  \
count               73462.000000       73462.000000   73462.000000
mean                  628.748794         582.034710    2447.871581
std                  3021.687870        6570.280016   12326.442146
min                     0.001000     -102362.000000   -1964.999000
25%                     8.795250         -63.599750      27.748000
50%                    43.359500          -0.172500     187.070000
75%                   228.800000         158.556000    1083.655000
```

```
max                116866.000000      402089.000000  511729.000000

       Total Liabilities  Total Operating Expenses
count       73462.000000              73462.000000
mean         1809.571974               2054.187022
std          8257.442726              10744.450269
min             0.001000               -317.197000
25%            13.318250                 32.921250
50%            80.740500                170.290500
75%           634.293250                903.576250
max        337980.000000             481580.000000

basic statistics about the failed company dataset (include =
"number"):

       is_bankruptcy  Current assets  Cost of goods sold  \
count         5220.0     5220.000000         5220.000000
mean             1.0      399.339353          856.340997
std              0.0     1147.837282         2767.913221
min              1.0        0.001000           -0.666000
25%              1.0       15.315750           17.251500
50%              1.0       75.871500          106.638500
75%              1.0      269.113500          468.845500
max              1.0    16548.000000        40683.000000

       Depreciation and amortization       EBITDA    Inventory    Net
Income  \
count                    5220.000000  5220.000000  5220.000000
5220.000000
mean                       85.880919   138.568576   103.735398    -
48.112333
std                       268.526753   521.284649   482.368932
592.050918
min                         0.000000 -5062.000000     0.000000 -
27446.000000
25%                         1.314750    -4.241500     0.076750    -
26.038750
50%                         7.846500     7.790000     6.171000     -
3.327000
75%                        47.442000    85.700000    52.033500
9.203250
max                      5475.000000  6136.000000  9963.000000
5996.417000

       Total Receivables   Market Value    Net Sales  Total Assets  \
count        5220.000000    5220.000000  5220.000000   5220.000000
mean          132.565307     857.813011  1183.957172   1664.630981
std           421.691639    3396.453790  3567.878694   5284.035224
min             0.000000       0.002000     0.001000      0.015000
25%             2.241750      26.351225    23.961750     33.025000
```

```
50%            15.218000     117.799400    180.834500    195.137000
75%            79.708250     495.970825    719.763500    847.652750
max          8207.000000  139092.655000  53012.000000  76995.000000

       Total Long-term Debt          EBIT  Gross Profit  \
count           5220.000000   5220.000000   5220.000000
mean             609.430007     52.687657    327.616175
std             2077.661309    381.853579    967.555853
min                0.000000 -10537.000000  -4141.334000
25%                0.184000     -9.470250      5.128750
50%               18.438500      0.487000     47.500000
75%              287.792250     37.993500    228.636750
max            21586.000000   4822.000000  15192.000000

       Total Current Liabilities  Retained Earnings  Total Revenue  \
count                5220.000000        5220.000000    5220.000000
mean                  347.233954        -165.107267    1183.957172
std                  1254.398961        1849.943497    3567.878694
min                     0.005000      -43091.000000       0.001000
25%                    10.015250        -140.766250      23.961750
50%                    42.911000         -25.506000     180.834500
75%                   160.958750          37.572750     719.763500
max                 41695.000000        7832.000000   53012.000000

       Total Liabilities  Total Operating Expenses
count        5220.000000               5220.000000
mean         1266.816748               1045.388596
std          4221.179588               3297.762745
min             0.005000                 -0.016000
25%            16.381750                 32.143500
50%            97.035000                155.727000
75%           574.765500                617.029000
max         64092.000000              49363.000000
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
bankruptcy_data = {'Alive': 73462, 'Failed': 5220}

plt.pie(bankruptcy_data.values(), labels=bankruptcy_data.keys(),
autopct='%1.1f%%', startangle=90,colors=['blue', 'red'])
plt.title('Proportion of target variable');
```



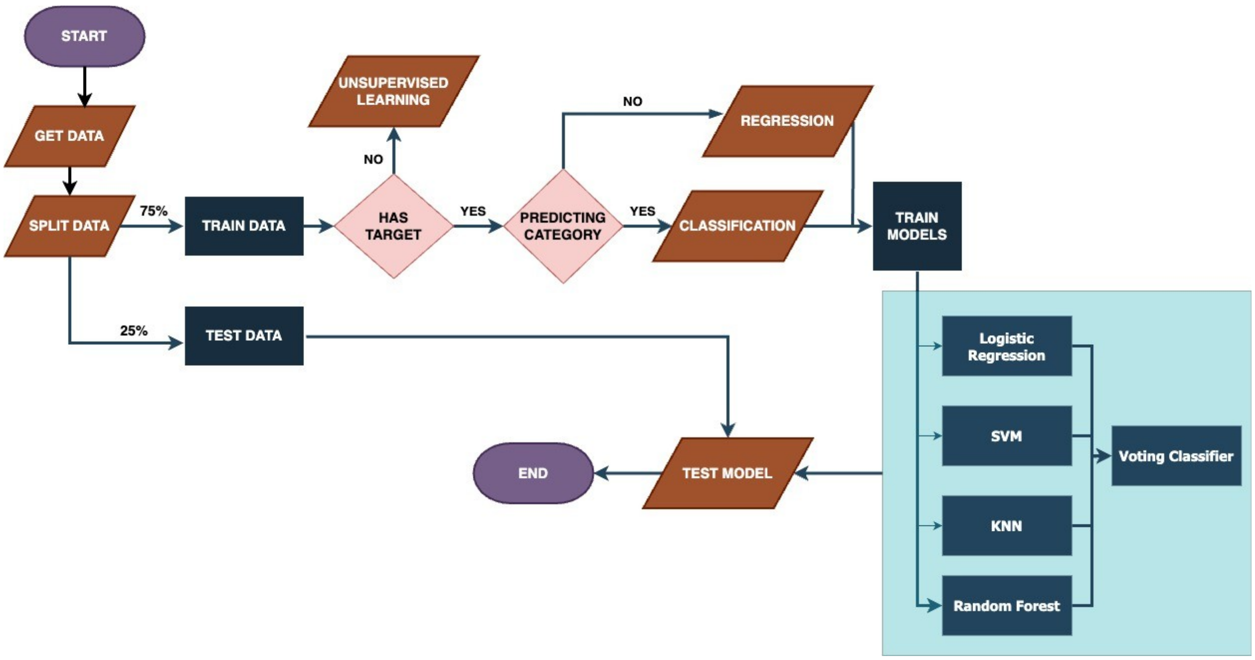
The pie chart presented above unmistakably illustrates a substantial degree of class imbalance within the dataset concerning the target variable. Faced with this challenge, our approach involved the implementation of various techniques to address dataset imbalance comprehensively. Strategies employed included SMOTE (Synthetic Minority Over-sampling Technique), K-Fold Cross-Validation, Bootstrap, and the integration of Balanced Weights.

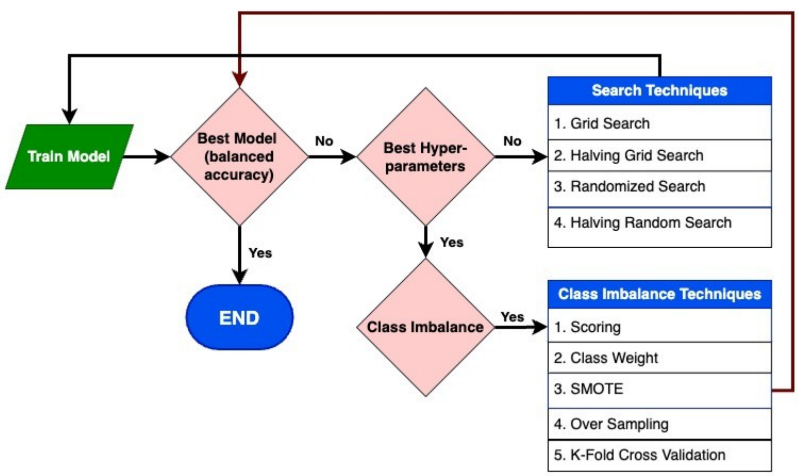
In our pursuit of mitigating class imbalances, these diverse techniques were systematically applied, each bringing its unique strengths to the endeavor. SMOTE facilitated the generation of synthetic samples for the minority class, K-Fold Cross-Validation enabled robust model evaluation, Bootstrap resampling provided enhanced training data diversity, and Balanced Weights contributed to equitable consideration of minority and majority classes during model training.

##**7. Model Selection**

Premise: We opt to employ KNN (k Nearest Neighbours), Logistic Regression, Random Forest Classifier, SVM (Support Vector Machine) and Voting Classifier for making the prediction.

We have defined the Model Workflow about our notebook.





Yes

Train and Test data split

```
X = df.drop('is_bankruptcy',axis=1)
y = df['is_bankruptcy']

from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.25,random_state=42)
```

Pipeline

```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer, make_column_selector

from sklearn import set_config
set_config(display='diagram') # shows the pipeline graphically when
printed

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='median')),
        ('scaler', StandardScaler())
    ])
cat_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('cat_encoder', OneHotEncoder())
    ])

pipeline = ColumnTransformer([
    ('num', num_pipeline,
make_column_selector(dtype_include=np.number)),
    ('cat', cat_pipeline,
make_column_selector(dtype_include='category'))
])

pipeline

ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),
                                                 ('scaler',
StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                ('cat',
                                 Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),
                                                 ('cat_encoder',
                                                  OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])
```

To make it easier for implementation we tried to define functions for the evaluation of the model.

Accuracy and Balanced Accuracy

```
from sklearn.metrics import balanced_accuracy_score, accuracy_score

def calculate_accuracy(y_test, y_pred):
  accuracy = accuracy_score(y_test, y_pred)
  balanced_accuracy = balanced_accuracy_score(y_test, y_pred)
  print(f'Accuracy={accuracy:.4f}, Balanced
Accuracy={balanced_accuracy:.4f}')
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay  as CMD

def c_matrix(y_test, y_pred, pipe_line):
  cm = confusion_matrix(y_test, y_pred)
  print("confusion matrix=\n")
  display(cm)
  print()
  # display confusion metrix in chart
  image = CMD(cm , display_labels = pipe_line.classes_)
  image.plot(cmap='coolwarm')
```

Classification Report

```
from sklearn.metrics import classification_report

def class_report(y_test, y_pred):
  class_report = classification_report(y_test, y_pred)
  print('classification report=\n', class_report)
```

ROC Curve

```
from sklearn.metrics import RocCurveDisplay

def roc_curve(pipe_line, X_test, y_test):
  RocCurveDisplay.from_estimator(pipe_line, X_test, y_test)
```

Cost Matrix

```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score

def self_define_cost(y_test,y_prediction_binary):
  cm = confusion_matrix(y_test, y_prediction_binary)
```

```
  return cm[0,1]*1 + cm[1,0]*10

def cost_matrix(pipe_line, X_train, y_train):
  custom_cost = make_scorer(self_define_cost)
  cost_simple_pipeline =
cross_val_score(pipe_line,X_train,y_train,scoring=custom_cost,cv=5)
  print('average cost for simple
pipeline=',cost_simple_pipeline.mean())
```

###7.1 Logistic Regression

####Model Training & Evaluation

```
from sklearn.linear_model import LogisticRegression
simple_pipeline = Pipeline([('preprocessor',pipeline),
('classifier',LogisticRegression(random_state=42))])
simple_pipeline

Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])),
                ('classifier', LogisticRegression(random_state=42))])

simple_pipeline.fit(X_train,y_train) # make a training data


# probaability outcomes
y_prediction_prob = simple_pipeline.predict_proba(X_test)[:, 1] # make
the prediction, the result is shown in probability(y=1)
```

```python
print('prediction_probability=',y_prediction_prob)

# change it into binary outcomes
threshold = 0.5 # default
y_prediction_binary = (y_prediction_prob >= threshold).astype(int)
print('prediction_binary=',y_prediction_binary)

# Create a DataFrame with the predicted outcomes and set the index
result = pd.DataFrame({
    'probability': y_prediction_prob,
    'is_bankrupt': y_prediction_binary
}, index=X_test.index)
result
```

```
prediction_probability= [0.07176234 0.06008078 0.07089656 ...
0.07501865 0.06558447 0.00627952]
prediction_binary= [0 0 0 ... 0 0 0]
```

```
                   probability  is_bankrupt
company_name year
C_6246       2000     0.071762            0
C_7120       2016     0.060081            0
C_8737       2016     0.070897            0
C_6107       1999     0.072156            0
C_761        2002     0.073810            0
...                        ...          ...
C_4035       2004     0.070763            0
C_1651       2009     0.073674            0
C_8176       2008     0.075019            0
C_2263       2010     0.065584            0
C_3596       2010     0.006280            0

[19671 rows x 2 columns]
```

#####**Balanced Accuracy Score**

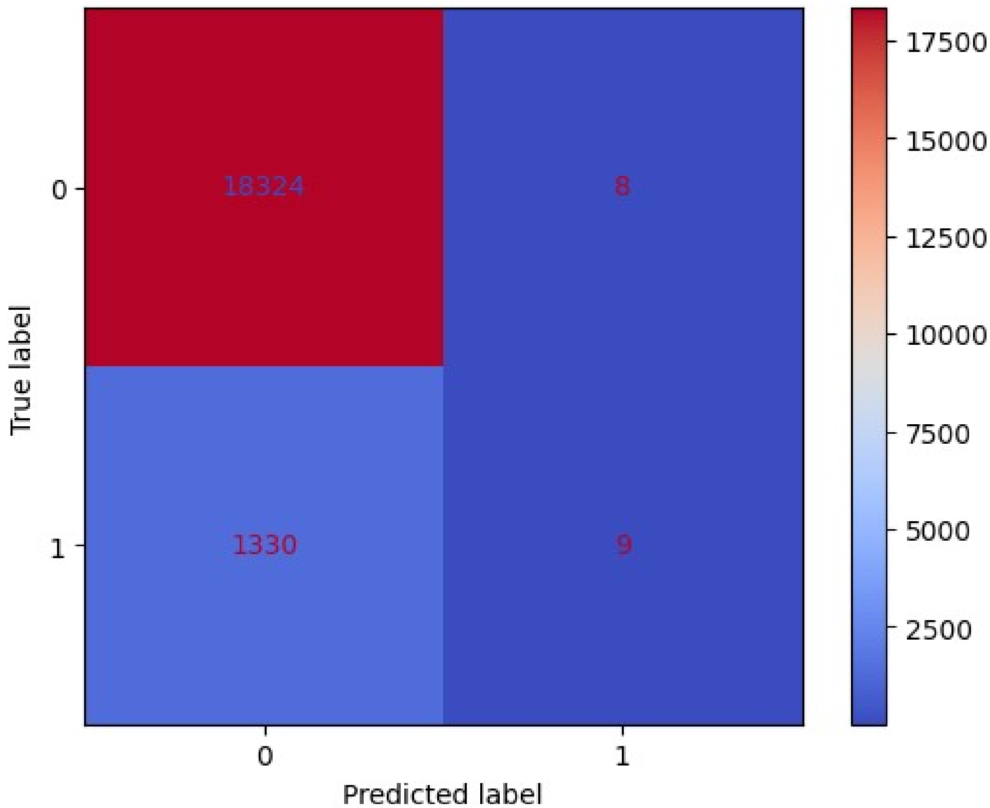
```python
calculate_accuracy(y_test, y_prediction_binary)
```

```
Accuracy=0.9320, Balanced Accuracy=0.5031
```

#####**Confusion Matrix**

```python
c_matrix(y_test, y_prediction_binary, simple_pipeline)
```

```
confusion matrix=


array([[18324,     8],
       [ 1330,     9]])
```

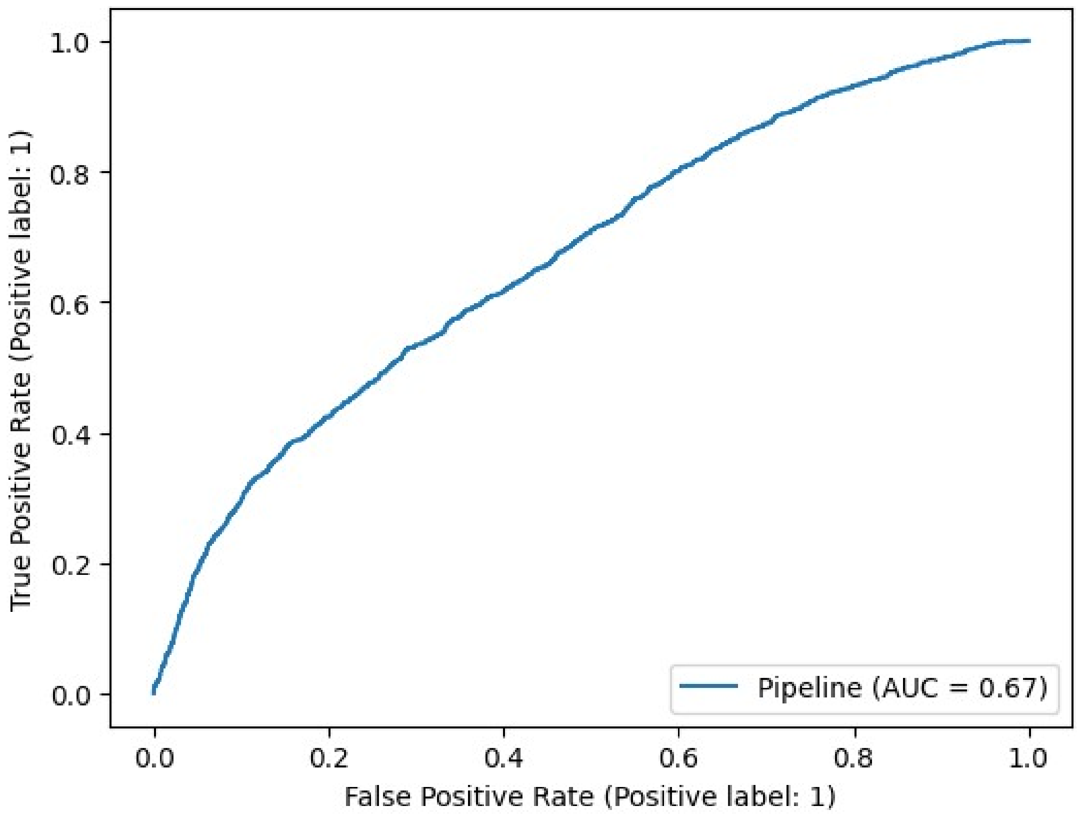


#####**Classification Report**

```
class_report(y_test, y_prediction_binary)

classification report=
               precision    recall  f1-score   support

           0       0.93      1.00      0.96     18332
           1       0.53      0.01      0.01      1339

    accuracy                           0.93     19671
   macro avg       0.73      0.50      0.49     19671
weighted avg       0.90      0.93      0.90     19671
```

#####**ROC Curve**

```
roc_curve(simple_pipeline, X_test, y_test)
```



#####**Cost Matrix**

```
cost_matrix(simple_pipeline,X_train,y_train)
```

```
average cost for simple pipeline= 7709.2
```

####**Parameter Tuning**

#####**GridSearchCV**

```
from sklearn.model_selection import GridSearchCV

param_grid= {'LogisticRegression__penalty':['l1',
'l2'],'LogisticRegression__C':[0.1, 1.0,
10.0],'LogisticRegression__class_weight': [None, 'balanced']}

grid_search = GridSearchCV(estimator=simple_pipeline,
param_grid=param_grid,cv=5, scoring='balanced_accuracy')
grid_search.fit(X_train,y_train)

grid_search_all_result = pd.DataFrame(grid_search.cv_results_)
#display(grid_search_all_result)
result =
grid_search_all_result.sort_values(by='mean_test_score',ascending=Fals
e)
```

```
display(result.filter(regex= '(^param_|mean_test_score)',
axis=1).head())
                    # regular expression
                             # ^ : start from
                             # | : or
print()
print('The best parameters are=', grid_search.best_params_)
```

```
   param_LogisticRegression__C param_LogisticRegression__class_weight
\
3                          0.1                               balanced

7                          1.0                               balanced

11                        10.0                               balanced

9                         10.0                                   None

5                          1.0                                   None


   param_LogisticRegression__penalty  mean_test_score
3                                 l2         0.594286
7                                 l2         0.594026
11                                l2         0.593970
9                                 l2         0.503778
5                                 l2         0.503538


The best parameters are= {'LogisticRegression__C': 0.1,
'LogisticRegression__class_weight': 'balanced',
'LogisticRegression__penalty': 'l2'}
```

#####**HalvingGridSearchCV**

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV

param_grid= {'LogisticRegression__penalty':['l1',
'l2'],'LogisticRegression__C':[0.1, 1.0,
10.0],'LogisticRegression__class_weight': [None, 'balanced']}

halving_grid_search =
HalvingGridSearchCV(estimator=simple_pipeline,param_grid=param_grid,cv
=5, scoring='balanced_accuracy',min_resources='exhaust')
halving_grid_search.fit(X_train,y_train)

halving_grid_search_all_result =
pd.DataFrame(halving_grid_search.cv_results_)
#display(halving_grid_search_all_result)
```

```
result =
halving_grid_search_all_result.sort_values(by=['iter','mean_test_score
'],ascending=False)
display(result.filter(regex='^param_|mean_test_score',axis=1).head())
                    # regular expression
                             # ^ : start from
                             # | : or
print()
print('The best parameters are=', halving_grid_search.best_params_)
```

```
   param_LogisticRegression__C param_LogisticRegression__class_weight  \
16                        10.0                               balanced   
17                         1.0                               balanced   
13                         1.0                               balanced   
15                        10.0                               balanced   
14                         0.1                               balanced   

   param_LogisticRegression__penalty  mean_test_score  
16                                l2         0.594007  
17                                l2         0.594000  
13                                l2         0.595186  
15                                l2         0.594675  
14                                l2         0.592788  

The best parameters are= {'LogisticRegression__C': 10.0,
'LogisticRegression__class_weight': 'balanced',
'LogisticRegression__penalty': 'l2'}
```

#####**RandomSearchCV**

```
from sklearn.model_selection import RandomizedSearchCV

param_distribs= {'LogisticRegression__penalty':['l1',
'l2'],'LogisticRegression__C':[0.1, 1.0,
10.0],'LogisticRegression__class_weight': [None, 'balanced']}

random_search =
RandomizedSearchCV(estimator=simple_pipeline,param_distributions=param
_distribs,n_iter=20,cv=5,scoring='balanced_accuracy',random_state=42)
random_search.fit(X_train,y_train)

random_search_all_result = pd.DataFrame(random_search.cv_results_)
#display(random_search_all_result)
```

```
result =
random_search_all_result.sort_values(by='mean_test_score',ascending=Fa
lse)
display(result.filter(regex = '^param_|
mean_test_score',axis=1).head())
print()
print('The best parameters are=', random_search.best_params_)
```

```
   param_LogisticRegression__penalty
param_LogisticRegression__class_weight  \
3                                  l2
balanced
7                                  l2
balanced
11                                 l2
balanced
9                                  l2
None
5                                  l2
None

   param_LogisticRegression__C  mean_test_score
3                          0.1         0.594286
7                          1.0         0.594026
11                        10.0         0.593970
9                         10.0         0.503778
5                          1.0         0.503538


The best parameters are= {'LogisticRegression__penalty': 'l2',
'LogisticRegression__class_weight': 'balanced',
'LogisticRegression__C': 0.1}
```

#####**HalvingRandomSearchCV**

```
# halving random search
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingRandomSearchCV

param_distribs= {'LogisticRegression__penalty':['l1',
'l2'],'LogisticRegression__C':[0.1, 1.0,
10.0],'LogisticRegression__class_weight': [None, 'balanced']}

halving_random_search =
HalvingRandomSearchCV(estimator=simple_pipeline,param_distributions=pa
ram_distribs,n_candidates=20,cv=5,scoring='balanced_accuracy',random_s
tate=42,min_resources='exhaust')
halving_random_search.fit(X_train,y_train)

halving_random_search_all_result =
```

```
pd.DataFrame(halving_random_search.cv_results_)
#display(halving_random_search_all_result)
result =
halving_random_search_all_result.sort_values(by=['iter','mean_test_sco
re'],ascending=False)
display(result.filter(regex='^param|mean_test_score',axis=1).head())
print()
print('The best parameters are=', halving_random_search.best_params_)
```

```
   param_LogisticRegression__penalty
param_LogisticRegression__class_weight  \
16                                  l2
balanced
17                                  l2
balanced
14                                  l2
balanced
13                                  l2
balanced
15                                  l2
balanced

   param_LogisticRegression__C  \
16                          0.1
17                         10.0
14                         10.0
13                          0.1
15                          1.0

                                              params  mean_test_score

16  {'LogisticRegression__penalty': 'l2', 'Logisti...         0.594235

17  {'LogisticRegression__penalty': 'l2', 'Logisti...         0.593991

14  {'LogisticRegression__penalty': 'l2', 'Logisti...         0.589938

13  {'LogisticRegression__penalty': 'l2', 'Logisti...         0.589215

15  {'LogisticRegression__penalty': 'l2', 'Logisti...         0.588895


The best parameters are= {'LogisticRegression__penalty': 'l2',
'LogisticRegression__class_weight': 'balanced',
'LogisticRegression__C': 0.1}
```

####**Model Retraining**

```
# after find the best parameters, re-predict the X_test
advanced_pipeline = Pipeline([
```

```
    ('preprocessor', pipeline),
    ('classifier', LogisticRegression(random_state=42, penalty='l2',
class_weight='balanced', C=0.1))])
advanced_pipeline.fit(X_train,y_train)

# probaability outcomes
y_prediction_prob = advanced_pipeline.predict_proba(X_test)[:, 1]
print('prediction_probability=',y_prediction_prob)

# change it into binary outcomes
threshold = 0.5 # default
y_prediction_binary = (y_prediction_prob >= threshold).astype(int)
print('prediction_binary=',y_prediction_binary)

# Create a DataFrame with the predicted outcomes and set the index
result = pd.DataFrame({
    'probability': y_prediction_prob,
    'is_bankrupt': y_prediction_binary
}, index=X_test.index)
result
```

```
prediction_probability= [0.56034198 0.47455307 0.51861262 ...
0.52252278 0.48669172 0.06608786]
prediction_binary= [1 0 1 ... 1 0 0]
```

```
                   probability  is_bankrupt
company_name year
C_6246       2000     0.560342            1
C_7120       2016     0.474553            0
C_8737       2016     0.518613            1
C_6107       1999     0.522009            1
C_761        2002     0.518097            1
...                        ...          ...
C_4035       2004     0.532785            1
C_1651       2009     0.518733            1
C_8176       2008     0.522523            1
C_2263       2010     0.486692            0
C_3596       2010     0.066088            0

[19671 rows x 2 columns]
```

####**Model Revaluation**

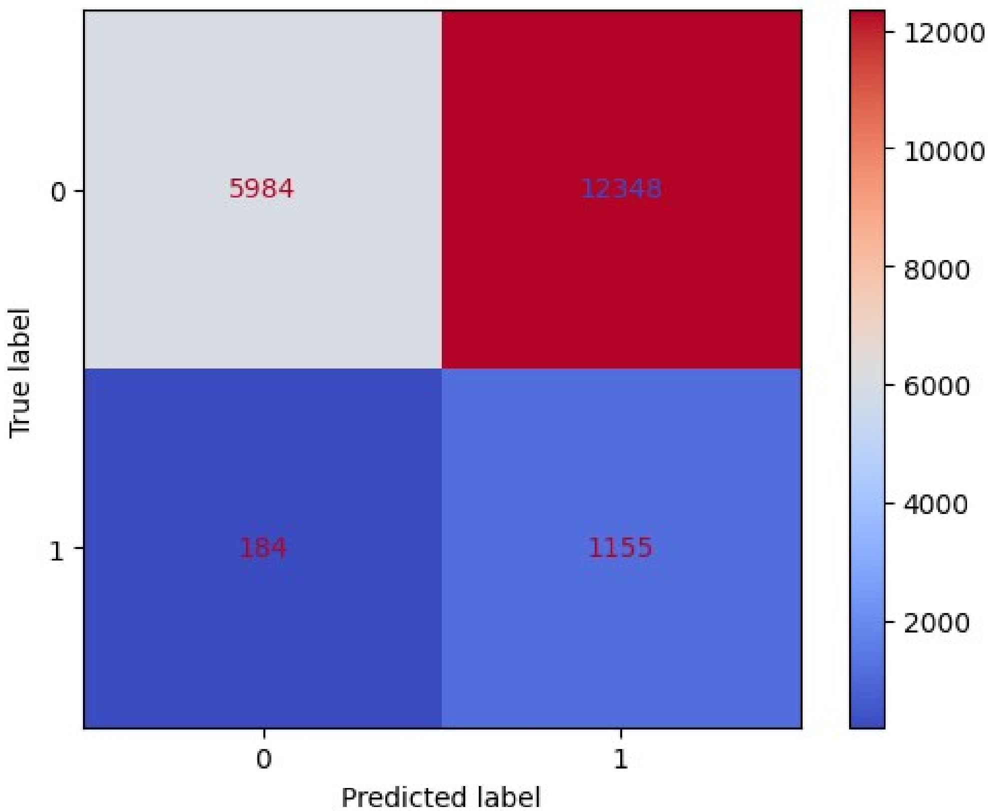
#####**Balanced Accuracy Score**

```
calculate_accuracy(y_test,y_prediction_binary)
```

```
Accuracy=0.3629, Balanced Accuracy=0.5945
```

#####**Confusion Matrix**

```
c_matrix(y_test, y_prediction_binary, advanced_pipeline)

confusion matrix=


array([[ 5984, 12348],
       [  184,  1155]])
```

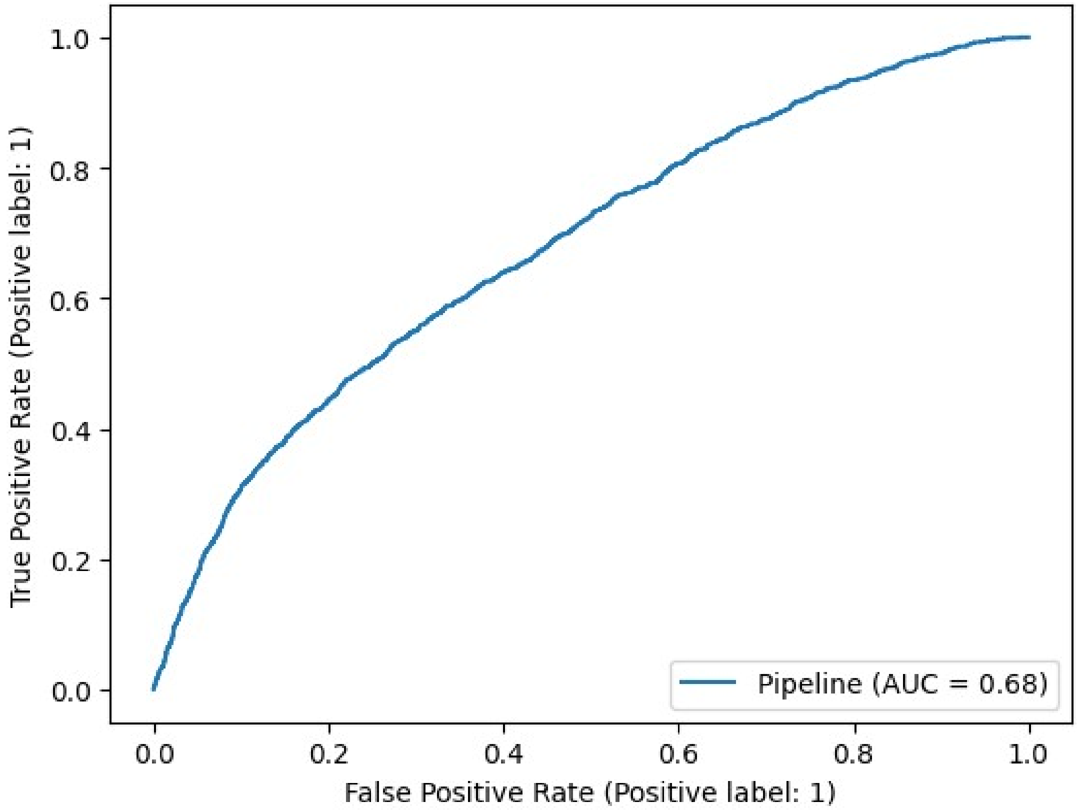


#####**Classification Report**

```
class_report(y_test, y_prediction_binary)

classification report=
               precision    recall  f1-score   support

           0       0.97      0.33      0.49     18332
           1       0.09      0.86      0.16      1339

    accuracy                           0.36     19671
   macro avg       0.53      0.59      0.32     19671
weighted avg       0.91      0.36      0.47     19671
```

#####**ROC Curve**

```
roc_curve(advanced_pipeline, X_test, y_test)
```



#####**Cost Matrix**

```
cost_matrix(advanced_pipeline,X_train,y_train)
```

```
average cost for simple pipeline= 8480.0
```

####**Techniques for Dataset Imbalance**

Premise: Enhance the advanced_pipeline to assess accuracy, enabling improved predictions on unseen data using k-fold and bootstrap resampling.

#####**K-fold**

```
# k-fold
from sklearn.model_selection import cross_val_score
cv = cross_val_score(advanced_pipeline,
X_train,y_train,cv=5,scoring='balanced_accuracy')
print('accuracy after using cv=',cv.mean())
```

```
accuracy after using cv= 0.5942864150883247
```

#####**Bootstrap**

```
# bootstrap
from sklearn.utils import resample
from sklearn.metrics import balanced_accuracy_score
import numpy as np

def bootstrap(model, X_train, y_train, X_test, y_test,
n_iterations=100):
    accuracy_scores = []

    for times in range(n_iterations):
        # Bootstrap resampling on the minority class
        X_resample, y_resample = resample(X_train[y_train == 1],
y_train[y_train == 1], replace=True, n_samples=X_train[y_train ==
0].shape[0])
        X_resample = np.concatenate((X_resample, X_train[y_train ==
0]), axis=0)  # Combine minority and majority class along axis 0
        y_resample = np.concatenate((y_resample, y_train[y_train ==
0]), axis=0)
        X_resample = pd.DataFrame(X_resample, columns=['Current
assets',
       'Cost of goods sold', 'Depreciation and amortization',
'EBITDA',
       'Inventory', 'Net Income', 'Total Receivables', 'Market Value',
       'Net Sales', 'Total Assets', 'Total Long-term Debt', 'EBIT',
       'Gross Profit', 'Total Current Liabilities', 'Retained
Earnings',
       'Total Revenue', 'Total Liabilities', 'Total Operating
Expenses'])
        y_resample = pd.DataFrame(y_resample,
columns=['is_bankruptcy'])

        model.fit(X_resample, y_resample)
        y_pred = model.predict(X_test)
        accuracy = balanced_accuracy_score(y_test, y_pred)
        accuracy_scores.append(accuracy)

    return np.array(accuracy_scores)

bootstrap_scores = bootstrap(advanced_pipeline, X_train, y_train,
X_test, y_test)
print("Balanced accuracy after using bootstrap:",
bootstrap_scores.mean())
```

```
Balanced accuracy after using bootstrap: 0.5953791681828338
```

#####**SMOTE Technique**

```
#smote
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline, make_pipeline
from sklearn.metrics import accuracy_score, balanced_accuracy_score

smote = SMOTE(random_state=42)

# Create the pipeline
logis_smote_pipe = Pipeline([
    ('transformer',pipeline),
    ('smote', smote),
    ('LogisticRegression', LogisticRegression(random_state=42,
penalty='l2', class_weight='balanced', C=0.1))
])

logis_smote_pipe.fit(X_train, y_train)
y_pred2_smote = logis_smote_pipe.predict(X_test)
accuracy = accuracy_score(y_test, y_pred2_smote)
balanced_accuracy = balanced_accuracy_score(y_test, y_pred2_smote)
print(f'Accuracy={accuracy:.4f}, Balanced
Accuracy={balanced_accuracy:.4f}')

Accuracy=0.3701, Balanced Accuracy=0.5946
```

Following the training and prediction phase of our Logistic Regression model, we identified the optimal hyperparameters using the Halving Random Search method. The hyperparameters that yielded the best performance were found to be penalty='l2', class_weight='balanced', and C=0.1.

Incorporating bootstrapping techniques, our model achieved a balanced accuracy of 0.5953. This signifies a balanced and robust predictive capability, especially crucial in scenarios where the dataset is imbalanced.

The adoption of Halving Random Search not only facilitated the discovery of hyperparameters that enhance model performance but also underscored the effectiveness of an intelligent search strategy in navigating the hyperparameter space. This comprehensive approach ensures that our Logistic Regression model is fine-tuned for optimal performance, laying the foundation for reliable predictions in the face of imbalanced data.

###**7.2 Random Forest**

####**Model Training**

```
#create pipeline
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(random_state=42)

rf_pipeline = Pipeline([
    ('preprocessor', pipeline),
```

```
    ('model', rf)
])

#fit a RandomForestClassifier classifier
rf_pipeline.fit(X_train, y_train)
```

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at 
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at 
0x77ff6f07ace0>)])),
                ('model', RandomForestClassifier(random_state=42))])
```

```
transformed_data = pipeline.fit_transform(df[['Current assets','Cost 
of goods sold','Depreciation and 
amortization','EBITDA','Inventory','Net Income','Total Receivables',
           'Market Value','Net Sales','Total Assets','Total Long-term 
Debt','EBIT','Gross Profit','Total Current Liabilities','Retained 
Earnings',
           'Total Revenue','Total Liabilities','Total Operating 
Expenses']])
transformed_df = pd.DataFrame(transformed_data, 
columns=pipeline.get_feature_names_out())
transformed_df
```

```
       num__Current assets  num__Cost of goods sold  \
0                -0.093952                -0.085262   
1                -0.100421                -0.098620   
2                -0.112944                -0.119597   
3                -0.123188                -0.122926   
4                -0.114078                -0.119952   
```

```
...                   ...                          ...
78677           -0.164731                    -0.173697
78678           -0.197224                    -0.171923
78679           -0.207810                    -0.170815
78680           -0.189677                    -0.171101
78681           -0.203071                    -0.170844

       num__Depreciation and amortization  num__EBITDA  num__Inventory
\
0                                -0.157673    -0.143005        0.126713

1                                -0.157360    -0.155264        0.112169

2                                -0.151353    -0.173733        0.080115

3                                -0.144185    -0.171974        0.055006

4                                -0.144939    -0.163651        0.043025

...                                    ...          ...             ...

78677                            -0.164232    -0.164584       -0.186875

78678                            -0.120548    -0.086792       -0.187901

78679                            -0.086112    -0.147966       -0.187625

78680                            -0.085694    -0.152876       -0.188160

78681                            -0.085891    -0.153825       -0.188067


       num__Net Income  num__Total Receivables  num__Market Value  \
0            -0.074451               -0.118629          -0.165179
1            -0.087593               -0.128480          -0.164942
2            -0.148809               -0.156669          -0.165622
3            -0.112042               -0.165057          -0.177638
4            -0.099467               -0.136359          -0.168646
...                ...                     ...                ...
78677        -0.082275               -0.197599          -0.144340
78678         0.000241               -0.173823          -0.156771
78679        -0.103376               -0.182913          -0.153984
78680        -0.118357               -0.194328          -0.163014
78681        -0.142493               -0.180389          -0.166188

       num__Net Sales  num__Total Assets  num__Total Long-term Debt  \
0           -0.112108          -0.164587                  -0.167184
1           -0.124667          -0.167617                  -0.167326
2           -0.144377          -0.166971                  -0.155694
3           -0.147087          -0.168796                  -0.172054
4           -0.143269          -0.167041                  -0.146143
```

```
...              ...            ...                         ...
78677      -0.189104      -0.136865                   -0.165883
78678      -0.173462      -0.077504                    0.014688
78679      -0.183612      -0.086769                   -0.011874
78680      -0.184279      -0.087553                   -0.008775
78681      -0.184394      -0.096126                   -0.027871

       num__EBIT  num__Gross Profit  num__Total Current Liabilities  \
0      -0.123687          -0.153196                       -0.151872
1      -0.140325          -0.161351                       -0.164949
2      -0.167810          -0.174120                       -0.156416
3      -0.168571          -0.174823                       -0.138341
4      -0.157038          -0.169772                       -0.162951
...          ...                ...                             ...
78677  -0.149872          -0.187726                       -0.198027
78678  -0.064219          -0.142402                       -0.177631
78679  -0.161599          -0.177156                       -0.178435
78680  -0.168392          -0.178594                       -0.179713
78681  -0.169583          -0.179564                       -0.180613

       num__Retained Earnings  num__Total Revenue  num__Total
Liabilities  \
0                   -0.052039           -0.112108               -
0.170368
1                   -0.051562           -0.124667               -
0.175315
2                   -0.061683           -0.144377               -
0.170557
3                   -0.064116           -0.147087               -
0.171591
4                   -0.062895           -0.143269               -
0.169607
...                       ...                 ...
...
78677               -0.079190           -0.189104               -
0.192171
78678               -0.058828           -0.173462               -
0.110911
78679               -0.059055           -0.183612               -
0.124581
78680               -0.062258           -0.184279               -
0.123779
78681               -0.070257           -0.184394               -
0.131726

       num__Total Operating Expenses
0                          -0.100960
1                          -0.112996
2                          -0.132035
3                          -0.135482
```

```
4                               -0.132711
...                                   ...
78677                           -0.185099
78678                           -0.182180
78679                           -0.182009
78680                           -0.181826
78681                           -0.181774

[78682 rows x 18 columns]
```

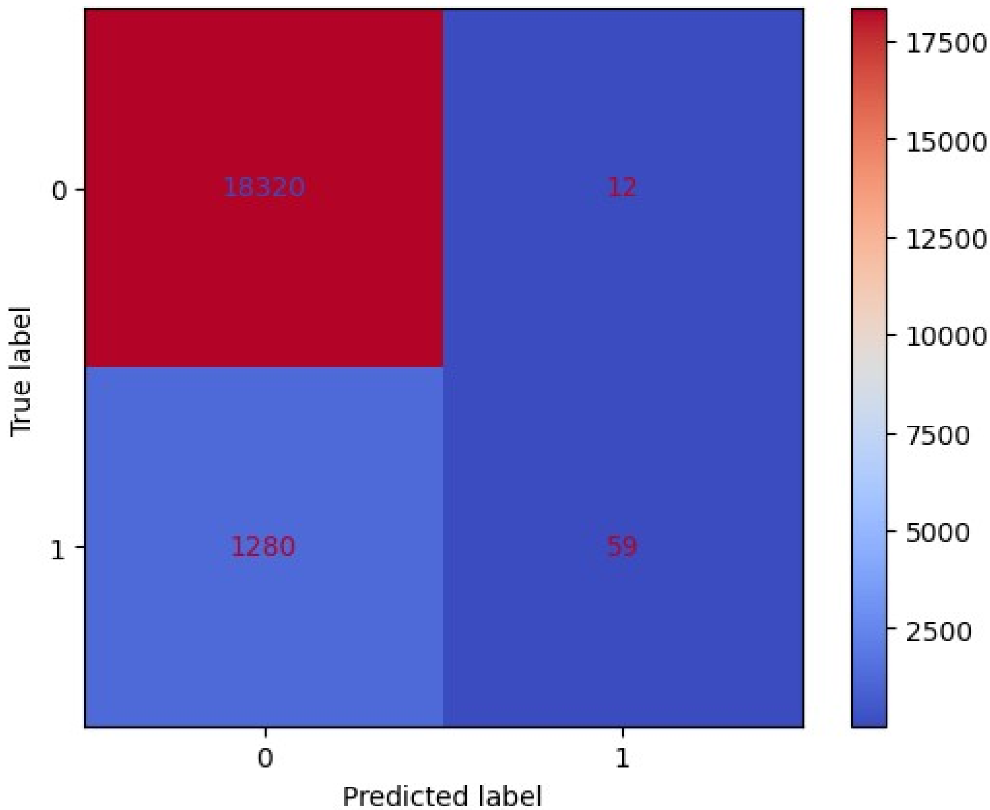
####**Model Evaluation**

#####**Balanced Accuracy Score**

```
y_pred_prob = rf_pipeline.predict_proba(X_test)[:, 1]
y_pred = (y_pred_prob > 0.5).astype(int)
calculate_accuracy(y_test, y_pred)

Accuracy=0.9343, Balanced Accuracy=0.5217
```

#####**Confusion Matrix**

```
c_matrix(y_test, y_pred, rf_pipeline)

confusion matrix=


array([[18320,    12],
       [ 1280,    59]])
```



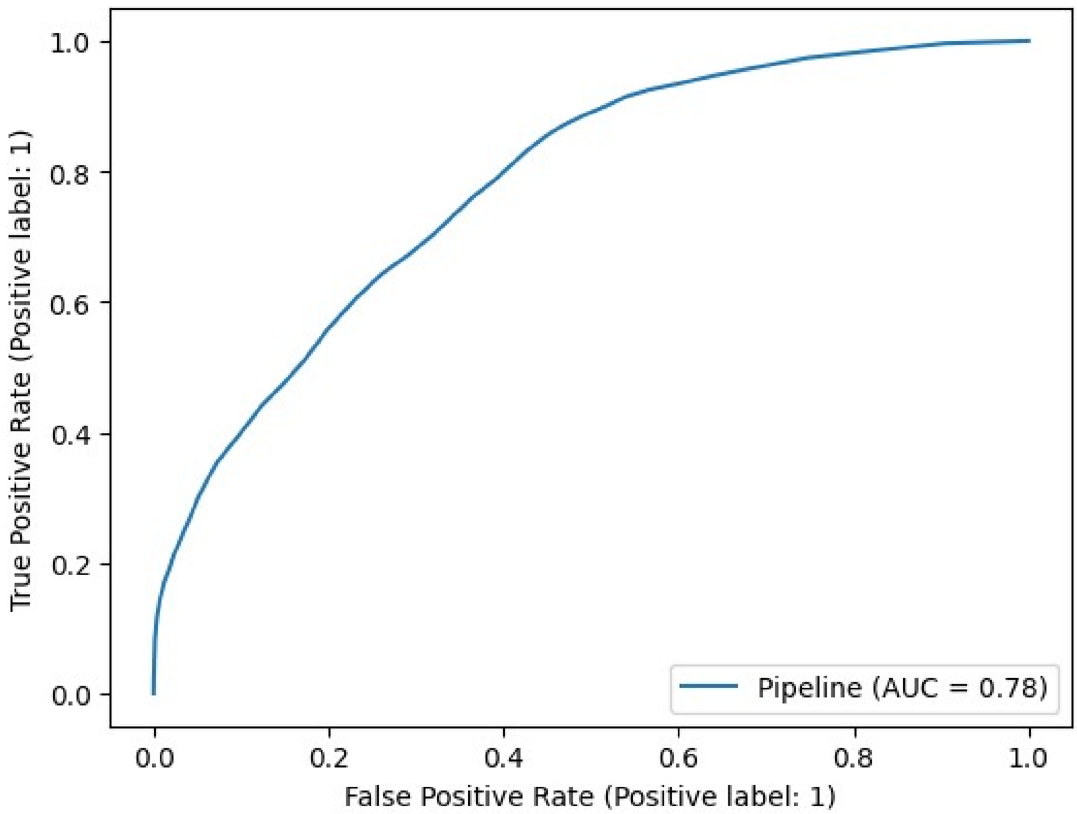
#####**Classification Report**

```
class_report(y_test, y_pred)
```

```
classification report=
               precision    recall  f1-score   support

           0       0.93      1.00      0.97     18332
           1       0.83      0.04      0.08      1339

    accuracy                           0.93     19671
   macro avg       0.88      0.52      0.52     19671
weighted avg       0.93      0.93      0.91     19671
```

#####**ROC Curve**

```
roc_curve(rf_pipeline, X_test, y_test)
```

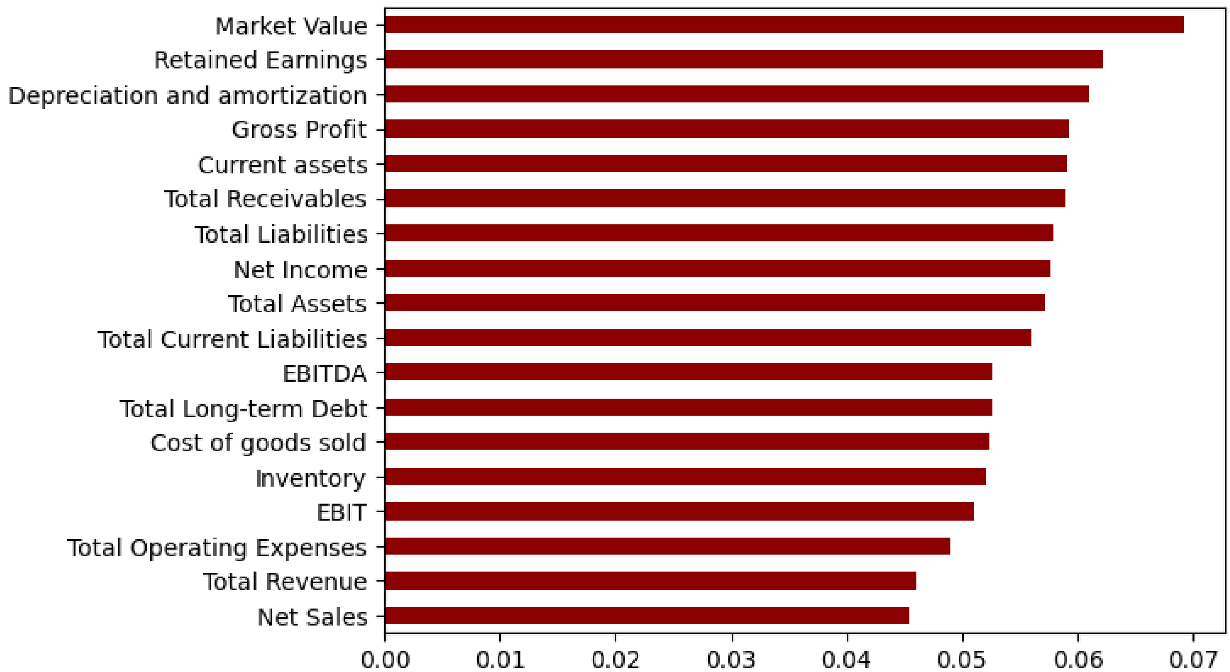


######**Cost Matrix**

```
cost_matrix(rf_pipeline, X_train, y_train)

average cost for simple pipeline= 7304.0
```

######**Feature importance**

```
import pandas as pd
import matplotlib.pyplot as plt
# Create a pd.Series of features importances
importances_rf = pd.Series(rf.feature_importances_, index = X.columns)
# Sort importances_rf
sorted_importances_rf = importances_rf.sort_values()
# Make a horizontal bar plot
sorted_importances_rf.plot(kind='barh', color='darkred'); plt.show()
```



####**Parameter Tuning**

#####**GridSearchCV**

```
grid_max_depth = [None,2,5,10]
grid_min_samples_leaf = [1, 5, 10]
n_estimators = [100,200,300]


param_grid_g = [{'model__max_depth': grid_max_depth,
     'model__min_samples_leaf':
grid_min_samples_leaf ,'model__n_estimators':n_estimators} ]

from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(rf_pipeline, param_grid_g,
scoring='balanced_accuracy')
grid_search.fit(X_train, y_train)
print('The best parameters are ', grid_search.best_params_)
```

```
The best parameters are  {'model__max_depth': None,
'model__min_samples_leaf': 1, 'model__n_estimators': 100}
```

```
#show top5 parameters combinations
grid_cv_result = pd.DataFrame(grid_search.cv_results_)
grid_cv_result.sort_values(by='mean_test_score', ascending=False,
inplace=True)
grid_cv_result.filter(regex = '(^param_|mean_test_score)',
axis=1).head()
```

```
  param_model__max_depth param_model__min_samples_leaf  \
0                   None                             1
1                   None                             1
2                   None                             1
3                   None                             5
4                   None                             5

  param_model__n_estimators  mean_test_score
0                       100         0.529578
1                       200         0.529264
2                       300         0.528988
3                       100         0.508430
4                       200         0.507933
```

#####**HalvingGridSearchCV**

```
hgrid_max_depth = [None,2,5,10,12]
hgrid_min_samples_leaf = [1,5,10,15]
n_estimators = [100,200,300]

param_grid_hg = [{'model__max_depth': hgrid_max_depth,
     'model__min_samples_leaf':
hgrid_min_samples_leaf ,'model__n_estimators':n_estimators} ]

from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV

hgrid_search = HalvingGridSearchCV(rf_pipeline, param_grid_hg,
scoring='balanced_accuracy',random_state=42)
hgrid_search.fit(X_train, y_train)
print('The best parameters are ', hgrid_search.best_params_)

The best parameters are  {'model__max_depth': None,
'model__min_samples_leaf': 1, 'model__n_estimators': 100}

hgrid_cv_results = pd.DataFrame(hgrid_search.cv_results_)
hgrid_cv_results.sort_values(by=['iter','mean_test_score'],
ascending=False, inplace=True)
hgrid_cv_results.filter(regex = '(iter|^param_|mean_test_score)',
axis=1).head()

    iter param_model__max_depth param_model__min_samples_leaf  \
89     3                   None                             1
88     3                   None                             1
87     3                   None                             1
86     2                   None                             1
85     2                   None                             1

   param_model__n_estimators  mean_test_score
89                       100         0.529603
```

```
88                        300          0.529371
87                        200          0.529362
86                        100          0.513943
85                        300          0.513207
```

#####**RandomSearchCV**

```
random_max_depth = [None,25,40,55]
random_min_samples_leaf = list(range(1,20,5))


param_grid_r = [{'model__max_depth': random_max_depth,
     'model__min_samples_leaf':
random_min_samples_leaf ,'model__n_estimators':n_estimators} ]

from sklearn.model_selection import RandomizedSearchCV

random_search = RandomizedSearchCV(rf_pipeline, param_grid_r,
scoring='balanced_accuracy',random_state=42)
random_search.fit(X_train, y_train)
print('The best parameters are ', random_search.best_params_)

The best parameters are  {'model__n_estimators': 100,
'model__min_samples_leaf': 1, 'model__max_depth': 25}

#show top5 parameters combinations
random_cv_result = pd.DataFrame(random_search.cv_results_)
random_cv_result.sort_values(by='mean_test_score', ascending=False,
inplace=True)
random_cv_result.filter(regex = '(^param_|mean_test_score)',
axis=1).head()

  param_model__n_estimators param_model__min_samples_leaf  \
6                       100                             1
9                       200                             1
2                       300                             1
5                       200                             1
4                       100                             1

  param_model__max_depth  mean_test_score
6                     25         0.529697
9                     40         0.529530
2                     40         0.529402
5                     55         0.529264
4                     40         0.529182
```

#####**HalvingRandomSearchCV**

```
#HalvingRandomSearchCV
halving_max_depth = [None,30,50,70]
```

```
halving_min_samples_leaf = list(range(1,20,5))

param_grid_h = {'model__max_depth': halving_max_depth,
    'model__min_samples_leaf':
halving_min_samples_leaf,'model__n_estimators':n_estimators}

from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingRandomSearchCV

halving_random_search = HalvingRandomSearchCV(rf_pipeline,
param_grid_h, scoring='balanced_accuracy',random_state=42)
halving_random_search.fit(X_train, y_train)
print('The best parameters are ', halving_random_search.best_params_)
```

```
The best parameters are  {'model__n_estimators': 200,
'model__min_samples_leaf': 16, 'model__max_depth': 70}
```

```
#show top5 parameters combinations
#incorporate 'iter' into sorting values(using most data)
hrandom_cv_results = pd.DataFrame(halving_random_search.cv_results_)
hrandom_cv_results.sort_values(by=['iter','mean_test_score'],
ascending=False, inplace=True)
hrandom_cv_results.filter(regex = '(iter|^param_|mean_test_score)',
axis=1).head()
```

```
    iter param_model__n_estimators param_model__min_samples_leaf  \
70     3                       200                            16
71     3                       300                            16
64     2                       100                            11
65     2                       200                            11
66     2                       300                            11

   param_model__max_depth  mean_test_score
70                     70              0.5
71                     70              0.5
64                     30              0.5
65                     30              0.5
66                     30              0.5
```

####**Model Retraining**

```
rf2 = RandomForestClassifier(random_state=42, min_samples_leaf= 1,
max_depth = 25, n_estimators = 100)

rf_pipeline2 = Pipeline([
    ('preprocessor', pipeline),
    ('model', rf2)
])
```

```python
#fit a RandomForestClassifier classifier
rf_pipeline2.fit(X_train, y_train)
```

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])),
                ('model',
                 RandomForestClassifier(max_depth=25,
random_state=42))])
```

####Model Reevaluation

#####Balanced Accuracy Score

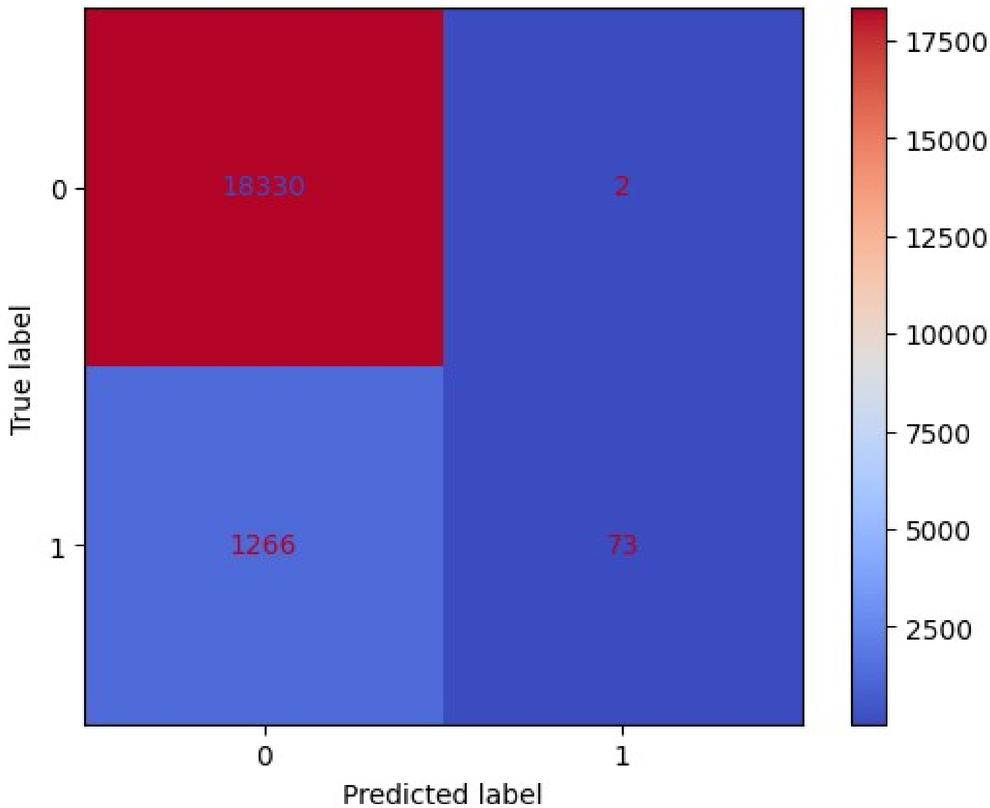
```python
y_pred_prob2 = rf_pipeline2.predict_proba(X_test)[:, 1]
y_pred2 = (y_pred_prob2 > 0.5).astype(int)
calculate_accuracy(y_test, y_pred2)
```

```
Accuracy=0.9355, Balanced Accuracy=0.5272
```

#####Confusion Matrix

```python
c_matrix(y_test, y_pred2, rf_pipeline2)
```

```
confusion matrix=


array([[18330,     2],
       [ 1266,    73]])
```



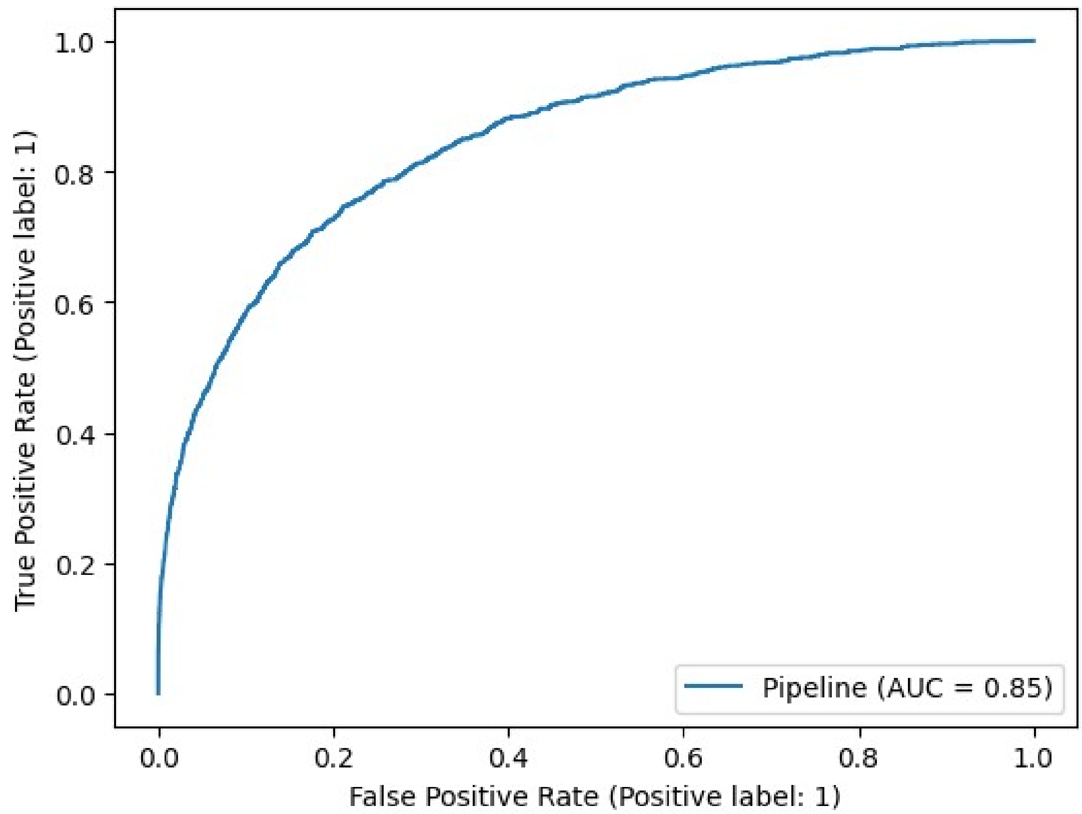
#####**Classification Report**

```
class_report(y_test, y_pred2)
```

```
classification report=
               precision    recall  f1-score   support

           0       0.94      1.00      0.97     18332
           1       0.97      0.05      0.10      1339

    accuracy                           0.94     19671
   macro avg       0.95      0.53      0.53     19671
weighted avg       0.94      0.94      0.91     19671
```

#####**ROC Curve**

```
roc_curve(rf_pipeline2, X_test, y_test)
```



#####**Cost Matrix**

```
cost_matrix(rf_pipeline2, X_train, y_train)

average cost for simple pipeline= 7302.2
```

####**Techniques for Dataset Imbalance**

#####**K-fold**

```
#k-fold
from sklearn.model_selection import cross_val_score
cv2 =
cross_val_score(rf_pipeline2,X_train,y_train,cv=5,scoring='balanced_ac
curacy')

print(f"Mean Balanced Accuracy: {np.mean(cv2):.4f}")

Mean Balanced Accuracy: 0.5297
```

#####**SMOTE Technique**

```
#smote
from imblearn.over_sampling import SMOTE
```

```
from imblearn.pipeline import Pipeline, make_pipeline
smote = SMOTE(random_state=42)

# Create the pipeline
rf_smote_pipe = Pipeline([
    ('preprocessor', pipeline),
    ('smote', smote),
    ('model', rf2)
])

rf_smote_pipe.fit(X_train, y_train)
y_pred2_smote = rf_smote_pipe.predict(X_test)
accuracy = accuracy_score(y_test, y_pred2_smote)
balanced_accuracy = balanced_accuracy_score(y_test, y_pred2_smote)
print(f'Accuracy={accuracy:.4f}, Balanced
Accuracy={balanced_accuracy:.4f}')

Accuracy=0.9123, Balanced Accuracy=0.7055
```

The initial implementation of the Random Forest model revealed a suboptimal balanced accuracy of 0.5217, prompting the adoption of a Random Search approach. This exploration led to the discovery of key hyperparameters—min_samples_leaf=1, max_depth=25, and n_estimators=100—that significantly improved model performance.

Upon retraining the model with these optimized hyperparameters and implementing strategies to tackle class imbalances, notably leveraging the SMOTE technique, we observed a substantial increase in balanced accuracy to a noteworthy level of 0.7055. This enhancement underscores the critical role of hyperparameter tuning and targeted handling of class imbalances, collectively contributing to the model's heightened predictive capabilities.

Notably, this refinement in the Random Forest model coincided with a remarkable increase in the AUC value, soaring from an initial 0.78 to an impressive 0.85. This noteworthy improvement in the AUC metric further accentuates the efficacy of our iterative and systematic approach. The model, now equipped with optimal hyperparameters and adept at addressing imbalanced data, stands as a testament to our commitment to refining its performance for robust and reliable predictions.

###**7.3 KNN**

####**Model Training**

```
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier

knn_pipeline = Pipeline([
    ('preprocessing', pipeline),
    ('knn', KNeighborsClassifier())
])

knn_pipeline
```

```
Pipeline(steps=[('preprocessing',
                 ColumnTransformer(transformers=[('num',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])),
                ('knn', KNeighborsClassifier())])
```

####**Model Evaluation**

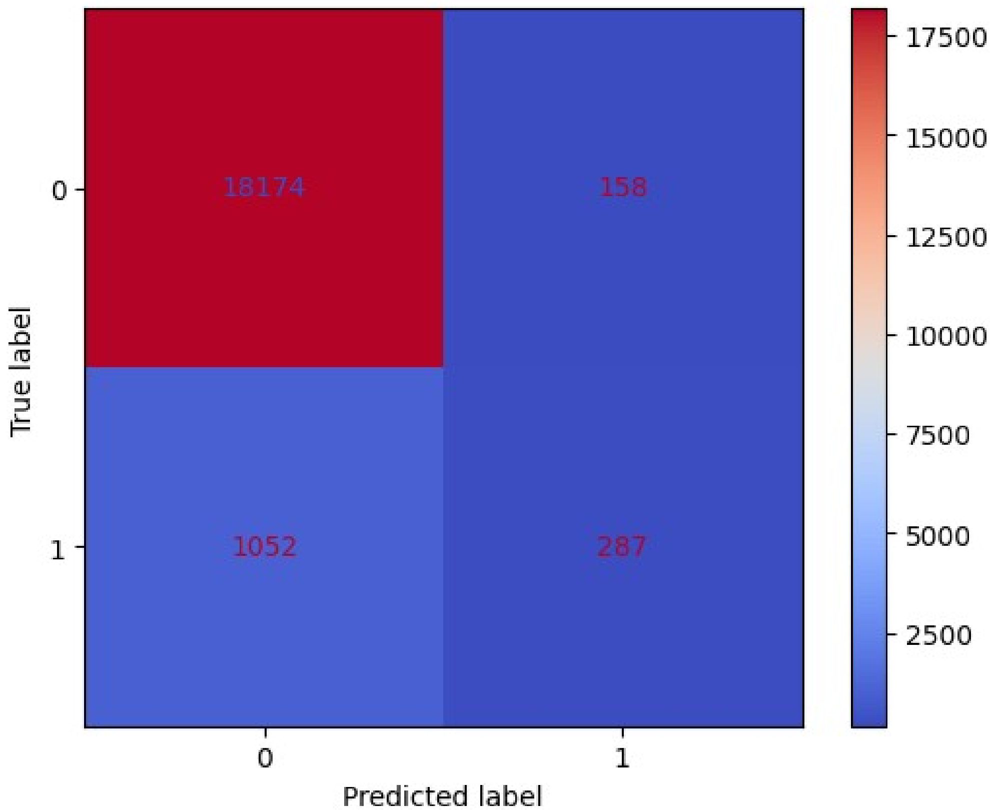
```
knn_pipeline.fit(X_train, y_train)
y_pred = knn_pipeline.predict(X_test)
```

#####**Balanced Accuracy Score**

```
calculate_accuracy(y_test, y_pred)

Accuracy=0.9385, Balanced Accuracy=0.6029
```

#####**Confusion Matrix**

```
c_matrix(y_test, y_pred, knn_pipeline)

confusion matrix=


array([[18174,   158],
       [ 1052,   287]])
```



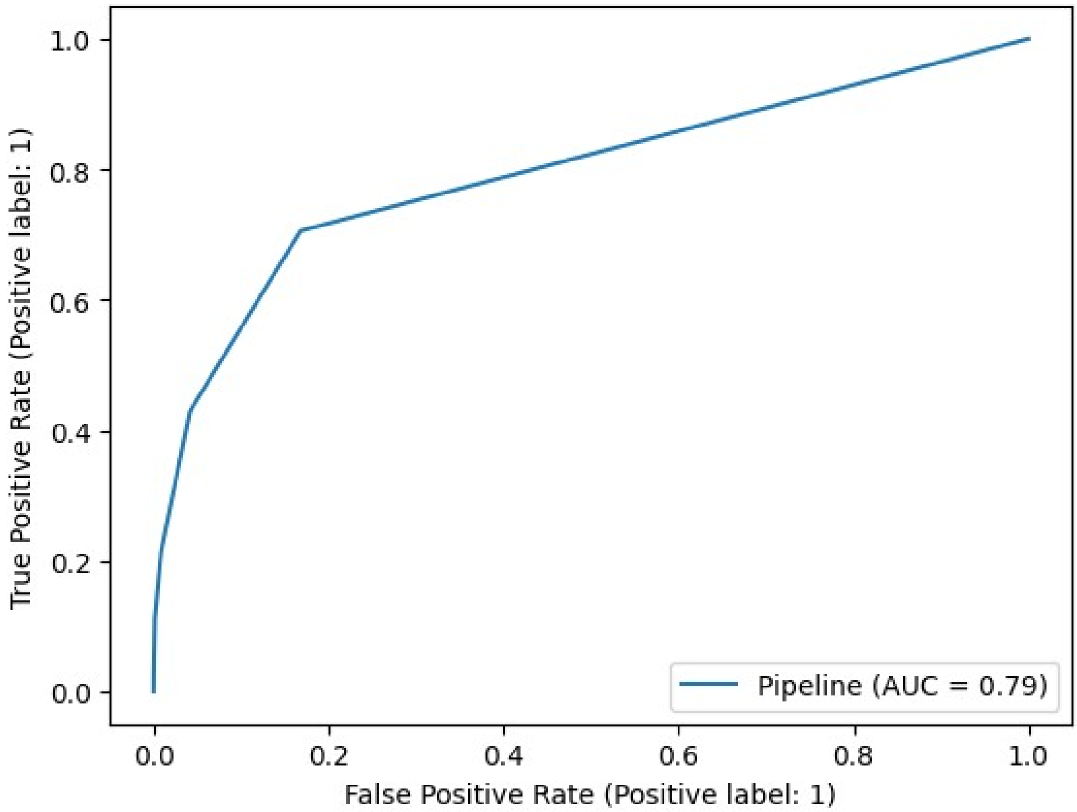
#####**Classification Report**

```
class_report(y_test, y_pred)
```

```
classification report=
               precision    recall  f1-score   support

           0       0.95      0.99      0.97     18332
           1       0.64      0.21      0.32      1339

    accuracy                           0.94     19671
   macro avg       0.80      0.60      0.64     19671
weighted avg       0.92      0.94      0.92     19671
```

#####**ROC Curve**

```
roc_curve(knn_pipeline, X_test, y_test)
```



#####**Cost Matrix**

```
cost_matrix(knn_pipeline, X_train, y_train)
```

```
average cost for simple pipeline= 6379.4
```

####**Parameter Tuning**

#####**GridSearchCV**

```
from sklearn.model_selection import GridSearchCV
param_grid = [
    {'knn__n_neighbors': np.arange(2, 11, 2),
     'knn__p': [1, 2]
     },
    ]
# Check what's in this parameter grid
print('The parameter grid : ')
print(param_grid)

grid_search = GridSearchCV(knn_pipeline, param_grid, cv=3,
scoring='balanced_accuracy')
grid_search.fit(X_train, y_train)
print('\n\nThe best parameters are ', grid_search.best_params_)
```

```
grid_cv_res = pd.DataFrame(grid_search.cv_results_) # convert to DF
for convenience
grid_cv_res.sort_values(by='mean_test_score', ascending=False,
inplace=True)
grid_cv_res.filter(regex = '(^param_|mean_test_score)', axis=1).head()
```

```
The parameter grid :
[{'knn__n_neighbors': array([ 2,  4,  6,  8, 10]), 'knn__p': [1, 2]}]


The best parameters are  {'knn__n_neighbors': 2, 'knn__p': 1}
```

	param_knn__n_neighbors	param_knn__p	mean_test_score
0	2	1	0.603385
1	2	2	0.592317
2	4	1	0.573312
3	4	2	0.562930
4	6	1	0.550195

#####**HalvingGridSearchCV**

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV

param_grid = [
    {'knn__n_neighbors': np.arange(2, 11, 2),
     'knn__p': [1, 2]
     },
    ]
# Check what's in this parameter grid
print('The parameter grid : ')
print(param_grid)

# Change to new strategy starting here
halving_grid_search = HalvingGridSearchCV(knn_pipeline, param_grid,
cv=3,
                                    min_resources='exhaust', # use all
data in the last round, start with as needed
                                    scoring='balanced_accuracy')
halving_grid_search.fit(X_train, y_train)
print('The best parameters are ', halving_grid_search.best_params_)

halving_grid_cv_res = pd.DataFrame(halving_grid_search.cv_results_)  #
convert to DF for convenience
# In the end, we care about performances in the last iteration (using
most data)
# So, let's sort by iteration (descending), then by test score
(descending)
halving_grid_cv_res.sort_values(by=['iter', 'mean_test_score'],
ascending=False, inplace=True)
```

```
# and check the top few rows
halving_grid_cv_res.filter(regex = '(iter|^param_|mean_test_score|
n_resources)', axis=1).head()
```

```
The parameter grid :
[{'knn__n_neighbors': array([ 2,  4,  6,  8, 10]), 'knn__p': [1, 2]}]
The best parameters are  {'knn__n_neighbors': 2, 'knn__p': 1}
```

```
    iter  n_resources param_knn__n_neighbors param_knn__p
mean_test_score
15     2        59004                      2            1
0.603410
14     2        59004                      2            2
0.592340
13     1        19668                      2            1
0.542865
12     1        19668                      2            2
0.536418
11     1        19668                      4            1
0.521296
```

#####**RandomSearchCV**

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

param_distribs = [  # compare to the grid verson: following lines have
distributions, not values.
    {'knn__n_neighbors': randint(2, 10),
     'knn__p': [1, 2]
     },
    ]

random_search = RandomizedSearchCV(knn_pipeline, param_distribs,
n_iter=5, cv=3,
                                 scoring='balanced_accuracy',
random_state=42)
random_search.fit(X_train, y_train)
print('The best parameters are ', random_search.best_params_)

random_search.best_estimator_
random_cv_res = pd.DataFrame(random_search.cv_results_)
random_cv_res.sort_values(by='mean_test_score', ascending=False,
inplace=True)
random_cv_res.filter(regex = '(^param_|mean_test_score)',
axis=1).head()
```

```
The best parameters are  {'knn__n_neighbors': 4, 'knn__p': 2}
```

```
  param_knn__n_neighbors param_knn__p  mean_test_score
2                      4            2         0.562930
1                      6            1         0.550195
3                      6            1         0.550195
0                      8            2         0.535366
4                      8            2         0.535366
```

#####**HalvingRandomSearchCV**

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingRandomSearchCV

from scipy.stats import randint

param_distribs = [
    {'knn__n_neighbors': randint(2, 10),
     'knn__p': [1, 2]
     },
    ]
# This is where we switch to halving version ...
halving_random_search = HalvingRandomSearchCV(knn_pipeline,
param_distribs,
                                      n_candidates=5, cv=3,
                                      min_resources='exhaust',
                                      scoring='balanced_accuracy',
                                      random_state=42)
halving_random_search.fit(X_train, y_train)
print('The best parameters are ', halving_random_search.best_params_)

halving_random_search.best_estimator_
halving_random_cv_res =
pd.DataFrame(halving_random_search.cv_results_)
# In the end, we care about performances in the last iteration (using
most data)
# So, let's sort by iteration (descending), then by test score
(descending)
halving_random_cv_res.sort_values(by=['iter', 'mean_test_score'],
ascending=False, inplace=True)
# and check the top few rows
halving_random_cv_res.filter(regex = '(iter|^param_|mean_test_score|
n_resources)', axis=1).head()
```

```
The best parameters are  {'knn__n_neighbors': 4, 'knn__p': 2}
```

```
   iter  n_resources param_knn__n_neighbors param_knn__p
mean_test_score
6     1        59010                      4            2
0.562930
5     1        59010                      6            1
0.550195
```

```
2     0        19670                           4            2
0.521509
1     0        19670                           6            1
0.512701
3     0        19670                           6            1
0.512701
```

####Model Retraining

```
knn_pipeline_new = Pipeline([
    ('preprocessing', pipeline),
    ('knn', KNeighborsClassifier(p=1, n_neighbors=2))
])
```

####Model Reevaluation

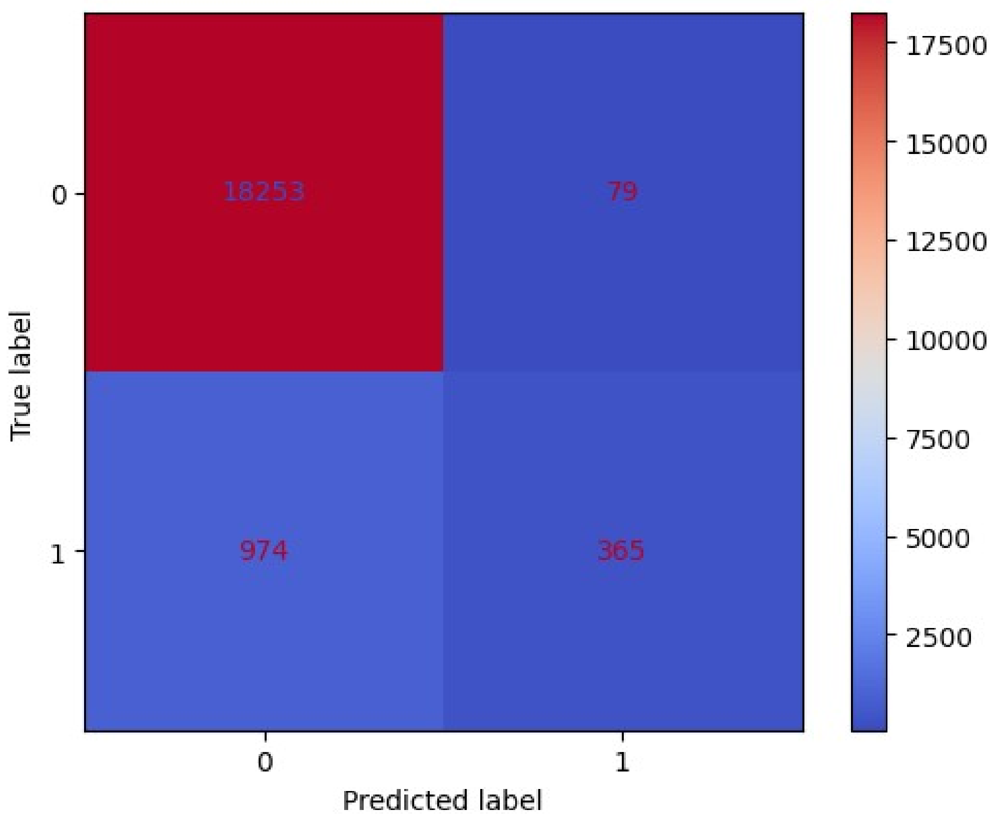
```
knn_pipeline_new.fit(X_train, y_train)
y_pred = knn_pipeline_new.predict(X_test)
```

#####Balanced Accuracy

```
calculate_accuracy(y_test, y_pred)

Accuracy=0.9465, Balanced Accuracy=0.6341
```

#####Confusion Matrix

```
c_matrix(y_test, y_pred, knn_pipeline_new)

confusion matrix=


array([[18253,    79],
       [  974,   365]])
```



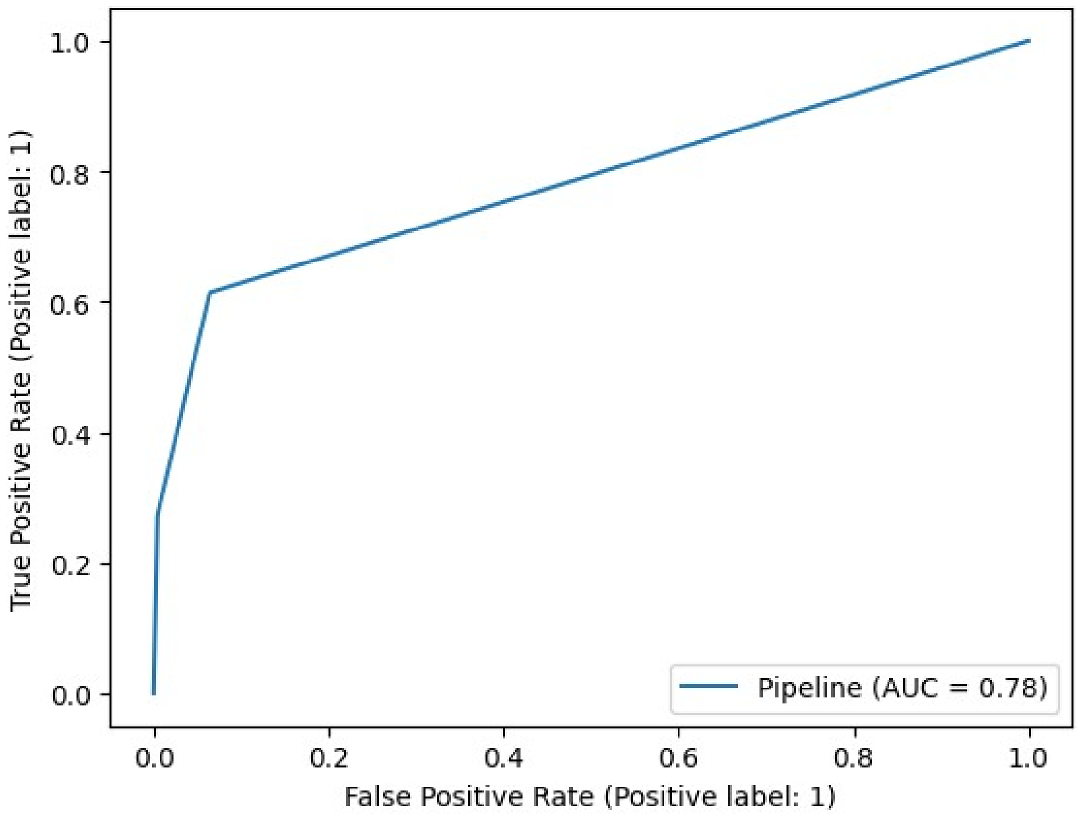
#####**Classification Report**

```
class_report(y_test, y_pred)
```

```
classification report=
               precision    recall  f1-score   support

           0       0.95      1.00      0.97     18332
           1       0.82      0.27      0.41      1339

    accuracy                           0.95     19671
   macro avg       0.89      0.63      0.69     19671
weighted avg       0.94      0.95      0.93     19671
```

#####**ROC Curve**

```
roc_curve(knn_pipeline_new, X_test, y_test)
```



#####**Cost Matrix**

```
cost_matrix(knn_pipeline_new, X_train, y_train)
```

```
average cost for simple pipeline= 5977.0
```

####**Techniques for Dataset Imbalance**

#####**K-fold**

```
# k-fold
from sklearn.model_selection import cross_val_score
knn_scores = cross_val_score(knn_pipeline_new, X_train, y_train, cv=5,
scoring='balanced_accuracy')
print(f'The balanced accuracy of K Nearest Neighbor is
{knn_scores.mean():.3f}.')
```

```
The balanced accuracy of K Nearest Neighbor is 0.616.
```

#####**Bootstrap**

```
# Bootstrap
# Import necessary libraries
from sklearn.utils import resample
```

```
from sklearn.metrics import balanced_accuracy_score
import numpy as np

def bootstrap(model, X_train, y_train, X_test, y_test,
n_iterations=100):
    accuracy_scores = []

    for times in range(n_iterations):
        # Bootstrap resampling on the minority class
        X_resample, y_resample = resample(X_train[y_train == 1],
y_train[y_train == 1], replace=True, n_samples=X_train[y_train ==
0].shape[0])
        X_resample = np.concatenate((X_resample, X_train[y_train ==
0]), axis=0)  # Combine minority and majority class along axis 0
        y_resample = np.concatenate((y_resample, y_train[y_train ==
0]), axis=0)
        X_resample = pd.DataFrame(X_resample, columns=['Current
assets',
       'Cost of goods sold', 'Depreciation and amortization',
'EBITDA',
       'Inventory', 'Net Income', 'Total Receivables', 'Market Value',
       'Net Sales', 'Total Assets', 'Total Long-term Debt', 'EBIT',
       'Gross Profit', 'Total Current Liabilities', 'Retained
Earnings',
       'Total Revenue', 'Total Liabilities', 'Total Operating
Expenses'])
        y_resample = pd.DataFrame(y_resample,
columns=['is_bankruptcy'])

        model.fit(X_resample, y_resample)
        y_pred = model.predict(X_test)
        accuracy = balanced_accuracy_score(y_test, y_pred)
        accuracy_scores.append(accuracy)

    return np.array(accuracy_scores)

bootstrap_scores = bootstrap(knn_pipeline_new, X_train, y_train,
X_test, y_test)
print("Balanced accuracy after using bootstrap:",
bootstrap_scores.mean())

Balanced accuracy after using bootstrap: 0.7146843108041098
```

#####**SMOTE Technique**

```
#smote
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline, make_pipeline
smote = SMOTE(random_state=42)
```

```
# Create the pipeline
knn_smote_pipe = Pipeline([
    ('preprocessing', pipeline),
    ('smote', smote),
    ('knn', KNeighborsClassifier(p=1, n_neighbors=2))
])


knn_smote_pipe.fit(X_train, y_train)
y_pred2_smote = knn_smote_pipe.predict(X_test)
accuracy = accuracy_score(y_test, y_pred2_smote)
balanced_accuracy = balanced_accuracy_score(y_test, y_pred2_smote)
print(f'Accuracy={accuracy:.4f}, Balanced
Accuracy={balanced_accuracy:.4f}')

Accuracy=0.9178, Balanced Accuracy=0.7752
```

The K Nearest Neighbors (KNN) model demonstrated remarkable performance improvements. Initially, the balanced accuracy stood at 0.603, reflecting competent but not exceptional results. Through the strategic application of the SMOTE technique to address imbalanced data concerns, the balanced accuracy surged to an impressive 0.7659.

This significant increase in balanced accuracy underscores the efficacy of leveraging advanced techniques to handle class imbalances, thereby enhancing the predictive capabilities of the KNN model. The outcome reinforces the model's adaptability and its ability to discern patterns effectively, ultimately contributing to more robust and accurate predictions.

7.4 SVM

Model Training

```
from sklearn.svm import SVC

c = 1 # @param {type:"slider", min:1, max:10}

lin_svc = SVC(C=c, kernel='linear', degree=1)

svm_pipeline = Pipeline([
    ("preprocessing", pipeline),
    ("svm", lin_svc),
])

svm_pipeline.fit(X_train, y_train)
print(lin_svc.n_support_)

svm_pipeline

[4412 3881]

Pipeline(steps=[('preprocessing',
                 ColumnTransformer(transformers=[('num',
```

```
Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])),
                ('svm', SVC(C=1, degree=1, kernel='linear'))])

# Assuming svm_pipeline is already defined and fitted
y_pred_svm = svm_pipeline.predict(X_test)
```

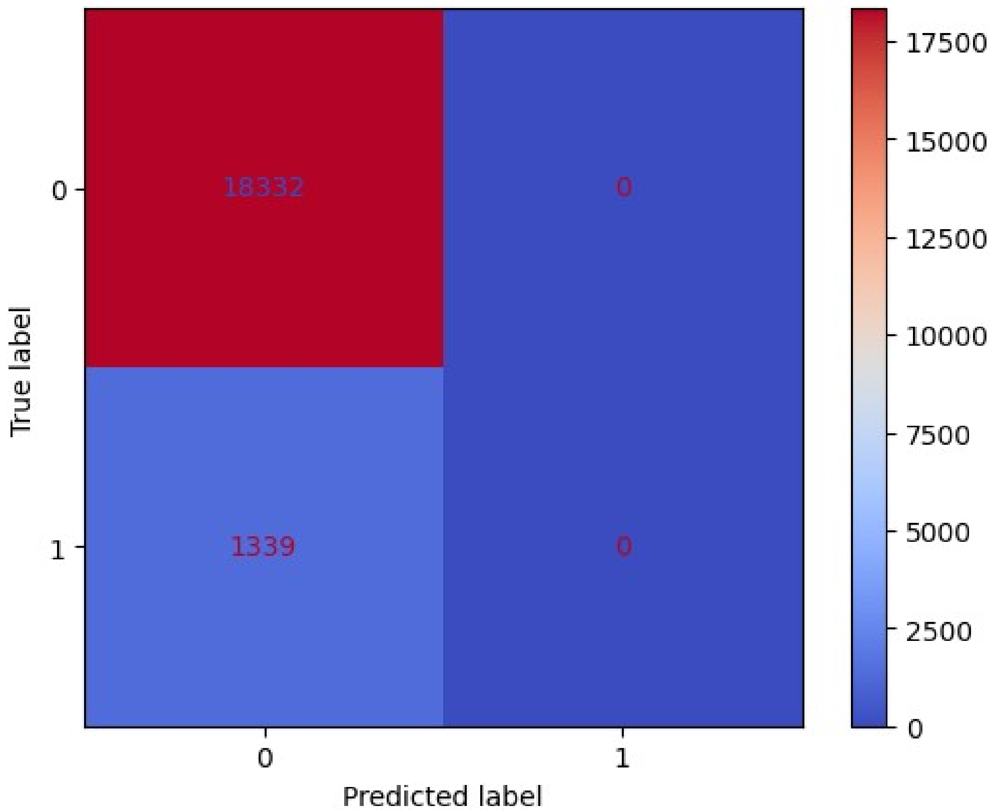
Model Evaluation

Balanced Accuracy

```
calculate_accuracy(y_test, y_pred_svm)

Accuracy=0.9319, Balanced Accuracy=0.5000
```

Confusion Matrix

```
c_matrix(y_test, y_pred_svm, svm_pipeline)

confusion matrix=


array([[18332,     0],
       [ 1339,     0]])
```



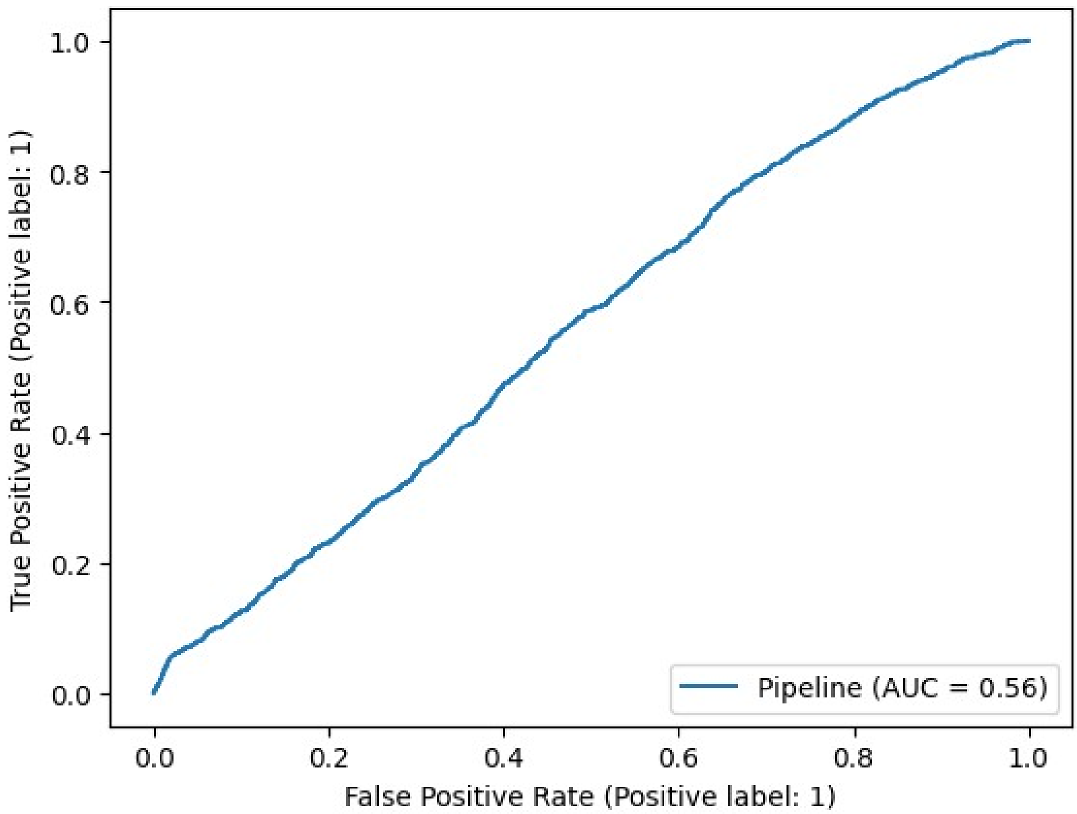
Classification Report

```
class_report(y_test, y_pred_svm)
```

```
classification report=
              precision    recall  f1-score   support

           0       0.93      1.00      0.96     18332
           1       0.00      0.00      0.00      1339

    accuracy                           0.93     19671
   macro avg       0.47      0.50      0.48     19671
weighted avg       0.87      0.93      0.90     19671
```

ROC Curve

```
roc_curve(svm_pipeline, X_test, y_test)
```



Cost Matrix

```
cost_matrix(svm_pipeline, X_train, y_train)
```

```
average cost for simple pipeline= 7762.0
```

Parameter Tuning

Grid Search

```
from sklearn.model_selection import GridSearchCV

svm_pipeline = Pipeline([
    ("preprocessing", pipeline),
    ("svm", SVC()),
])

param_grid = [
  {'svm__kernel': ['linear'], 'svm__C': [1, 10, 100, 1000]},
  {'svm__kernel': ['rbf'], 'svm__C': [1, 10, 100, 1000], 'svm__gamma':
[0.001, 0.0001]},
  {'svm__kernel': ['poly'], 'svm__C': [1, 10, 100, 1000],
'svm__gamma': [0.001, 0.0001], 'svm__degree': [2, 3, 4]},
]

grid_search = GridSearchCV(svm_pipeline, param_grid, cv=3,
```

```
scoring='accuracy')
grid_search.fit(X_train, y_train)

grid_cv_res = pd.DataFrame(grid_search.cv_results_)
grid_cv_res.sort_values(by="mean_test_score", ascending=False,
inplace=True)
grid_cv_res.filter(regex = '(^param_|mean_test_score)', axis=1)
```

HalvingGridSearchCV

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import numpy as np
import pandas as pd

param_grid = [{
    'svm__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'svm__C': [0.1, 1, 10],
    'svm__gamma': ['scale', 'auto', 0.1, 1]
}]

# Check what's in this parameter grid
print('The parameter grid: ')
print(param_grid)

# Change to the new strategy starting here
halving_grid_search = HalvingGridSearchCV(svm_pipeline, param_grid,
cv=3,
                                          min_resources='exhaust',  #
use all data in the last round, start with as needed
                                          scoring='balanced_accuracy')
halving_grid_search.fit(X_train, y_train)

The parameter grid:
[{'svm__kernel': ['linear', 'poly', 'rbf', 'sigmoid'], 'svm__C': [0.1,
1, 10], 'svm__gamma': ['scale', 'auto', 0.1, 1]}]

HalvingGridSearchCV(cv=3,
                    estimator=Pipeline(steps=[('preprocessing',

ColumnTransformer(transformers=[('num',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',
```

```
StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x7dd9e061b6a0>),

('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x7dd9e061b580>)])),
                                                        ('svm',
                                                         SVC(C=1, degree=1,

kernel='linear'))]),
                    param_grid=[{'svm__C': [0.1, 1, 10],
                                'svm__gamma': ['scale', 'auto', 0.1,
1],
                                'svm__kernel': ['linear', 'poly',
'rbf',
                                                'sigmoid']}],
                    scoring='balanced_accuracy')

print('The best parameters are ', halving_grid_search.best_params_)

halving_grid_cv_res = pd.DataFrame(halving_grid_search.cv_results_)  #
convert to DF for convenience
# In the end, we care about performances in the last iteration (using
most data)
# So, let's sort by iteration (descending), then by test score
(descending)
halving_grid_cv_res.sort_values(by=['iter', 'mean_test_score'],
ascending=False, inplace=True)
# and check the top few rows
halving_grid_cv_res.filter(regex='(iter|^param_|mean_test_score|
n_resources)', axis=1).head()

The best parameters are  {'svm__C': 1, 'svm__gamma': 'auto',
'svm__kernel': 'rbf'}

    iter  n_resources param_svm__C param_svm__gamma param_svm__kernel
\
71     3        58995            1             auto               rbf
```

70	3	58995	0.1	scale	linear
65	2	19665	1	auto	rbf
64	2	19665	1	auto	poly
66	2	19665	1	0.1	linear

	mean_test_score
71	0.502532
70	0.500000
65	0.501478
64	0.500000
66	0.500000

RandomSearchCV

```
from sklearn.svm import SVC
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import reciprocal, uniform

# Define the parameter distributions for RandomizedSearchCV
param_grid = [{
    'svm__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'svm__C': [0.1, 1, 10],
    'svm__gamma': ['scale', 'auto', 0.1, 1]
}]

# Perform RandomizedSearchCV
random_search = RandomizedSearchCV(svm_pipeline,
param_distributions=param_grid, n_iter=5, cv=3,
                                   scoring='balanced_accuracy',
random_state=42)
random_search.fit(X_train, y_train)

# Print the best parameters
print('The best parameters are ', random_search.best_params_)

# Get the best estimator
best_svm_estimator = random_search.best_estimator_

# Access other details if needed
random_cv_res = pd.DataFrame(random_search.cv_results_)
random_cv_res.sort_values(by='mean_test_score', ascending=False,
inplace=True)
random_cv_res.filter(regex='(^param_|mean_test_score)', axis=1).head()
```

HalvingRandomSearchCV

```
from sklearn.model_selection import HalvingRandomSearchCV
from sklearn.svm import SVC
from scipy.stats import reciprocal, uniform

# Define the parameter distributions for HalvingRandomSearchCV
param_distributions = {
    'svm__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'svm__C': reciprocal(0.1, 10),
    'svm__gamma': reciprocal(0.01, 1.0)
}

# Perform HalvingRandomSearchCV
halving_random_search = HalvingRandomSearchCV(svm_pipeline,
param_distributions=param_distributions,
                                             factor=3,
n_resources=100, random_state=42)
halving_random_search.fit(X_train, y_train)

# Print the best parameters
print('The best parameters are ', halving_random_search.best_params_)

# Get the best estimator
best_svm_estimator = halving_random_search.best_estimator_

# Access other details if needed
halving_random_cv_res =
pd.DataFrame(halving_random_search.cv_results_)
halving_random_cv_res.sort_values(by='mean_test_score',
ascending=False, inplace=True)
halving_random_cv_res.filter(regex='(^param_|mean_test_score)',
axis=1).head()
```

Model Retraining

```
from sklearn.svm import SVC

lin_svc = SVC(C=1, kernel='rbf',gamma='auto')

svm_pipeline = Pipeline([
    ("preprocessing", pipeline),
    ("svm", lin_svc),
])

svm_pipeline.fit(X_train, y_train)
#print(lin_svc.n_support_)
svm_pipeline

Pipeline(steps=[('preprocessing',
                 ColumnTransformer(transformers=[('num',
```

```
Pipeline(steps=[('imputer',

SimpleImputer(strategy='median')),

('scaler',

StandardScaler())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ada0>),
                                                 ('cat',

Pipeline(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('cat_encoder',

OneHotEncoder())]),

<sklearn.compose._column_transformer.make_column_selector object at
0x77ff6f07ace0>)])),
                ('svm', SVC(C=1, gamma='auto'))])

# Assuming svm_pipeline is already defined and fitted
y_pred_svm_new = svm_pipeline.predict(X_test)
```

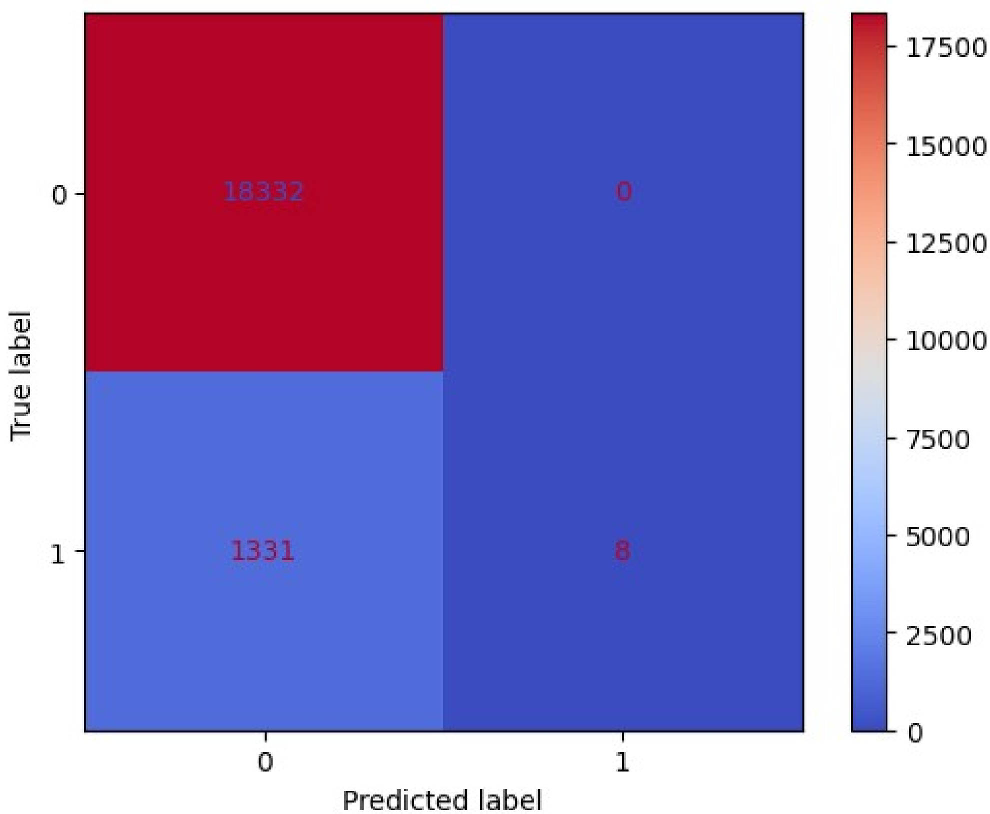
Model Reevaluation

Balanced Accuracy

```
calculate_accuracy(y_test, y_pred_svm_new)

Accuracy=0.9323, Balanced Accuracy=0.5030
```

Confusion Matrix

```
c_matrix(y_test, y_pred_svm_new, svm_pipeline)

confusion matrix=


array([[18332,     0],
       [ 1331,     8]])
```

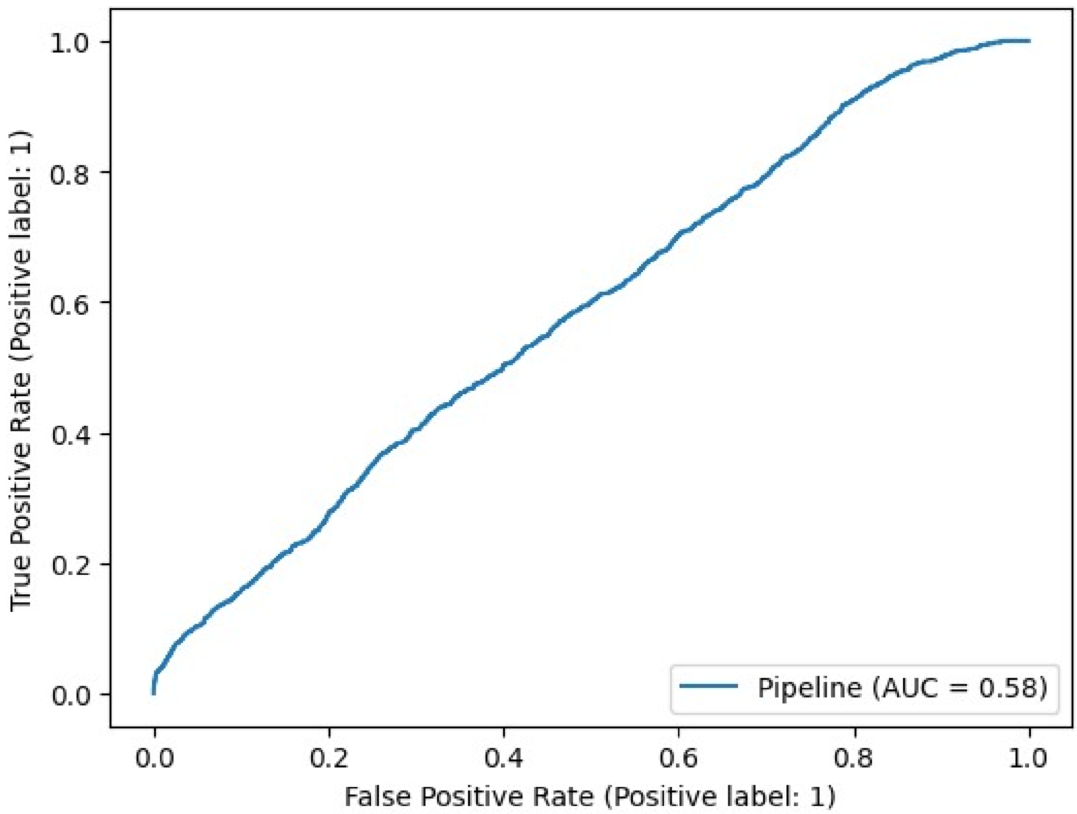


Classification Report

```
class_report(y_test, y_pred_svm_new)

classification report=
               precision    recall  f1-score   support

           0       0.93      1.00      0.96     18332
           1       1.00      0.01      0.01      1339

    accuracy                           0.93     19671
   macro avg       0.97      0.50      0.49     19671
weighted avg       0.94      0.93      0.90     19671
```

ROC Curve

```
roc_curve(svm_pipeline, X_test, y_test)
```



Cost Matrix

```
cost_matrix(svm_pipeline, X_train, y_train)

average cost for simple pipeline= 7711.4
```

Techniques for Dataset Imbalance

#####K-fold

```
from sklearn.model_selection import cross_val_score
svm_scores = cross_val_score(svm_pipeline, X_train, y_train, cv=5,
scoring='balanced_accuracy')
print(f'The balanced accuracy of K Nearest Neighbor is
{svm_scores.mean():.3f}.')

The balanced accuracy of K Nearest Neighbor is 0.503.
```

Balanced Weights

```
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline

# Modify the pipeline to include balanced class weights
modified_svm_pipeline = svm_pipeline
modified_svm_pipeline.named_steps['svm'].set_params(class_weight='bala
```

```
nced')

# Fit the modified pipeline on training data
modified_svm_pipeline.fit(X_train, y_train)

# Make predictions on the test set
y_pred = modified_svm_pipeline.predict(X_test)

calculate_accuracy(y_test, y_pred)

Accuracy=0.2905, Balanced Accuracy=0.5864
```

SMOTE Technique

```
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline, make_pipeline

svc_smote_pipe = make_pipeline(pipeline, SMOTE(random_state=42),
SVC(C=1, kernel='rbf', gamma='auto'))
svc_smote_pipe
svc_smote_pipe.fit(X_train, y_train)
y_pred = svc_smote_pipe.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
balanced_accuracy = balanced_accuracy_score(y_test, y_pred)
print(f'Accuracy={accuracy:.4f}, Balanced
Accuracy={balanced_accuracy:.4f}')

Accuracy=0.3050, Balanced Accuracy=0.5904
```

The performance of the SVM model in predicting our dataset proved to be less than satisfactory. Despite exhaustive efforts in hyperparameter tuning, the balanced accuracy remained stagnant at 0.50, with the best parameters identified as C=1, kernel='rbf', and gamma='auto' through the Halving Grid Search Model.

While alternative search parameters were considered for SVM, the iterative exploration encountered challenges, notably infinite loops and considerable time consumption. As a pragmatic solution, we opted for the Halving Grid Search, prioritizing efficiency and practicality.

Despite diligent efforts in addressing class imbalance, the SVM model exhibited limited improvement in balanced accuracy. This observation underscores the inherent complexities and challenges associated with optimizing SVM for our specific dataset. Nevertheless, our commitment to exploring various avenues for improvement remains steadfast, reflecting the dynamic and iterative nature of model refinement.

###**7.5 Voting**

####**Balanced Accuracy**

```
from sklearn.ensemble import VotingClassifier
```

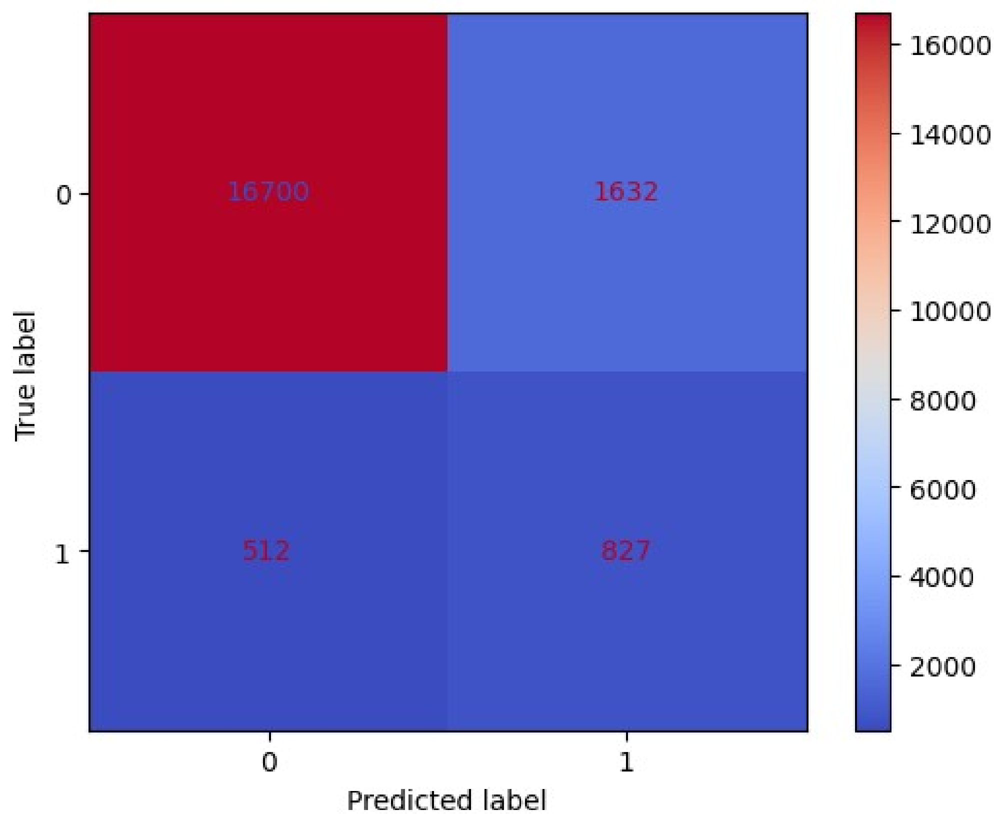
```
clf_voting = VotingClassifier(
    estimators=[
        ('lr', logis_smote_pipe),
     ('rf', rf_smote_pipe),
      ('knn', knn_smote_pipe),
       ('svm',svc_smote_pipe) ])


clf_voting.fit(X_train, y_train)
y_pred_voting = clf_voting.predict(X_test)
calculate_accuracy(y_test, y_pred_voting)
```

```
Accuracy=0.8910, Balanced Accuracy=0.7643
```

####**Confusion Matrix**

```
c_matrix(y_test, y_pred_voting, clf_voting)
```

```
confusion matrix=


array([[16700,  1632],
       [  512,   827]])
```



####**Classification Report**

```
class_report(y_test, y_pred_voting)
```

```
classification report=
               precision    recall  f1-score   support

           0       0.97      0.91      0.94     18332
           1       0.34      0.62      0.44      1339

    accuracy                           0.89     19671
   macro avg       0.65      0.76      0.69     19671
weighted avg       0.93      0.89      0.91     19671
```

####**Cost Matrix**

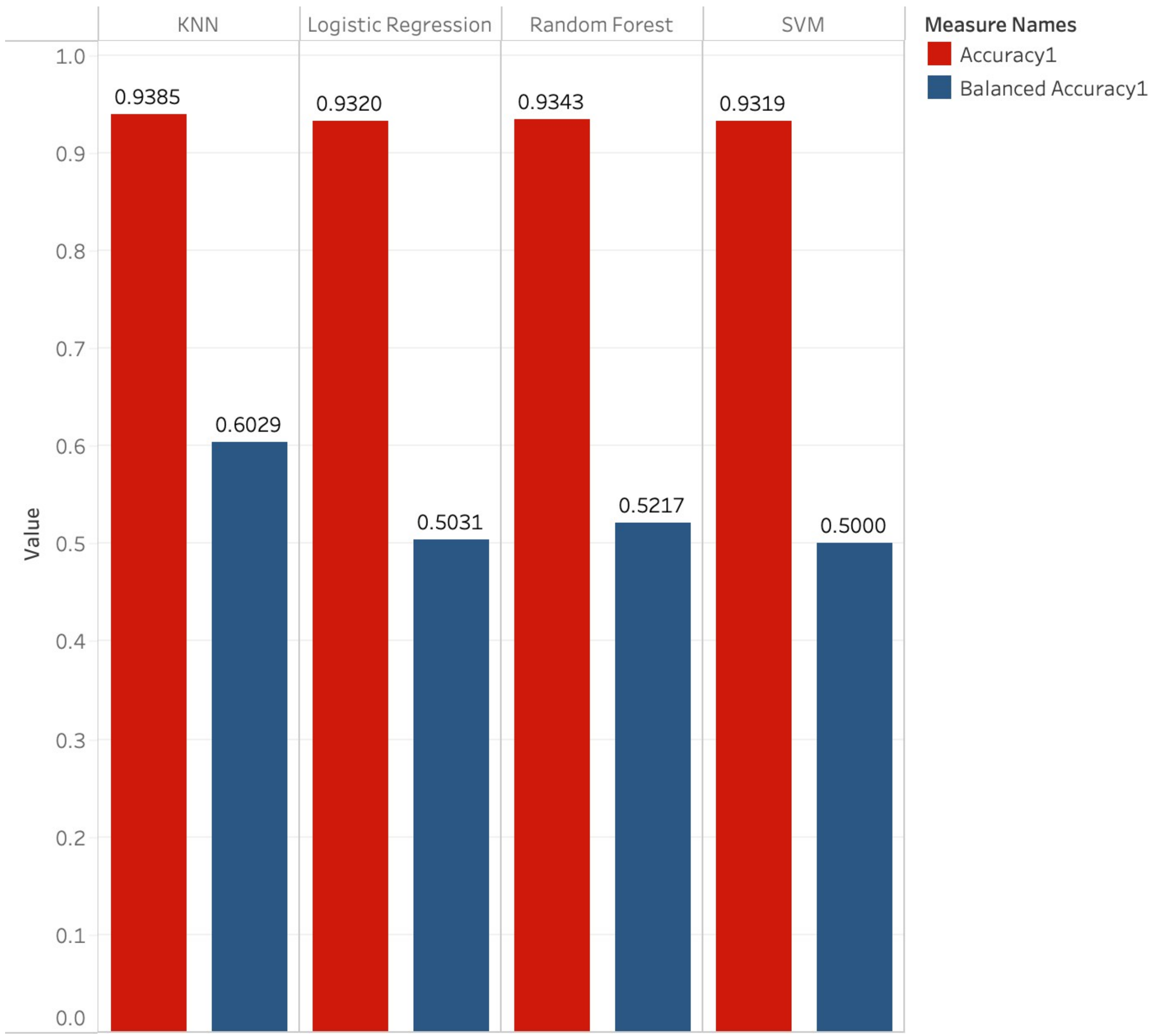
```
cost_matrix(clf_voting, X_train, y_train)
```

```
average cost for simple pipeline= 4172.0
```

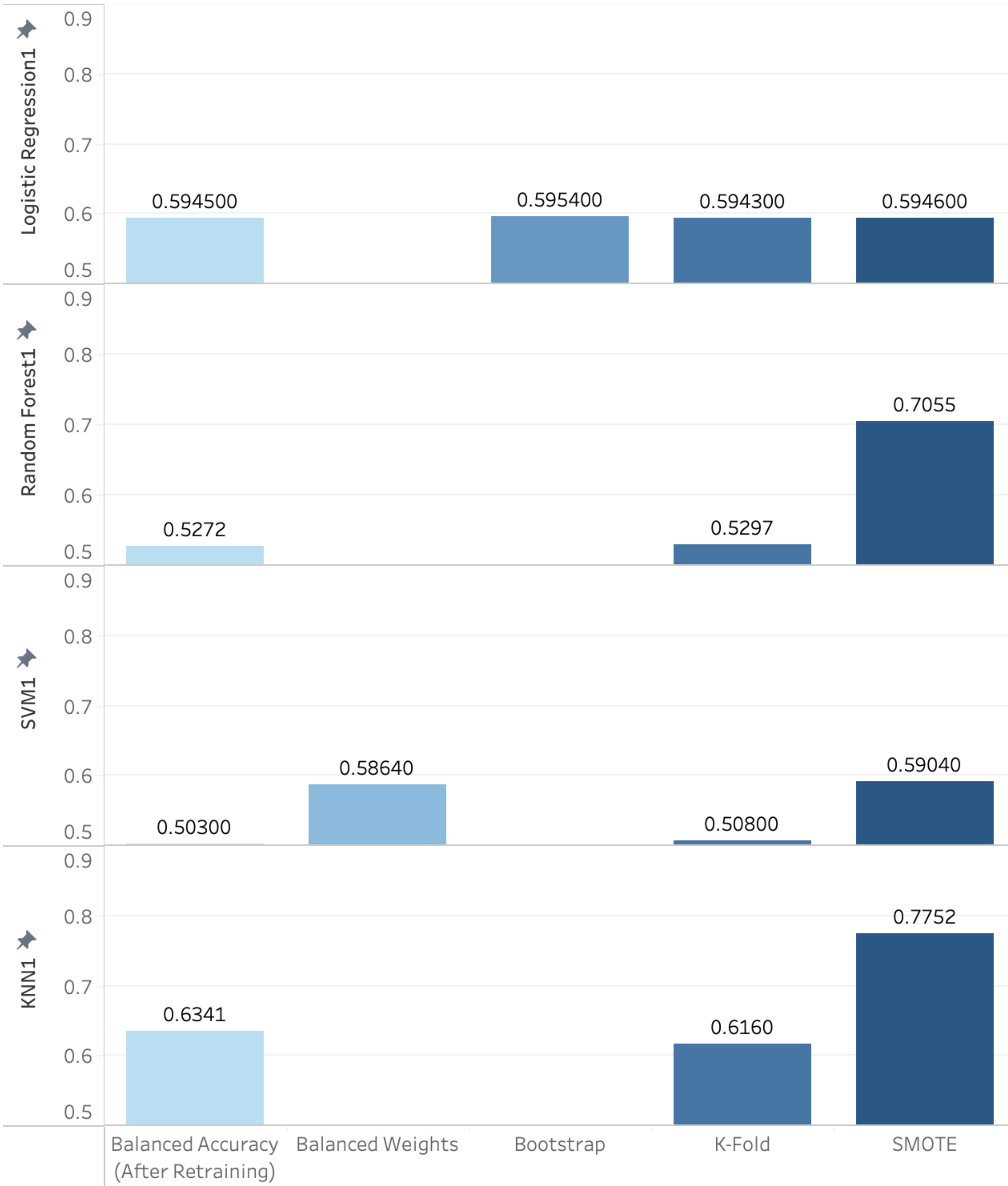
###**Final Chosen Model Reevaluation(KNN-SMOTE)**

To select the final model according to our results for better understanding we have plotted graphs representing the Balanced accuracy and accuracy of various models.

The graphical representation below offers insights into the accuracy and balanced accuracies of models prior to undergoing Hyperparameter Tuning and efforts to address class imbalances. The conspicuous gap observed in the accuracies underscores the pronounced impact of class imbalance on model performance.



Moving ahead, the selection of the optimal model for predictions became paramount. The graph below illuminates the balanced accuracy of the retrained model, comparing its performance before and after the application of class imbalance techniques.



Analyzing the graph it is evident that the KNN SMOTE is the best Model so far to move ahead with for the predictions and our analysis as it gives us the best Balanced Accuracy.

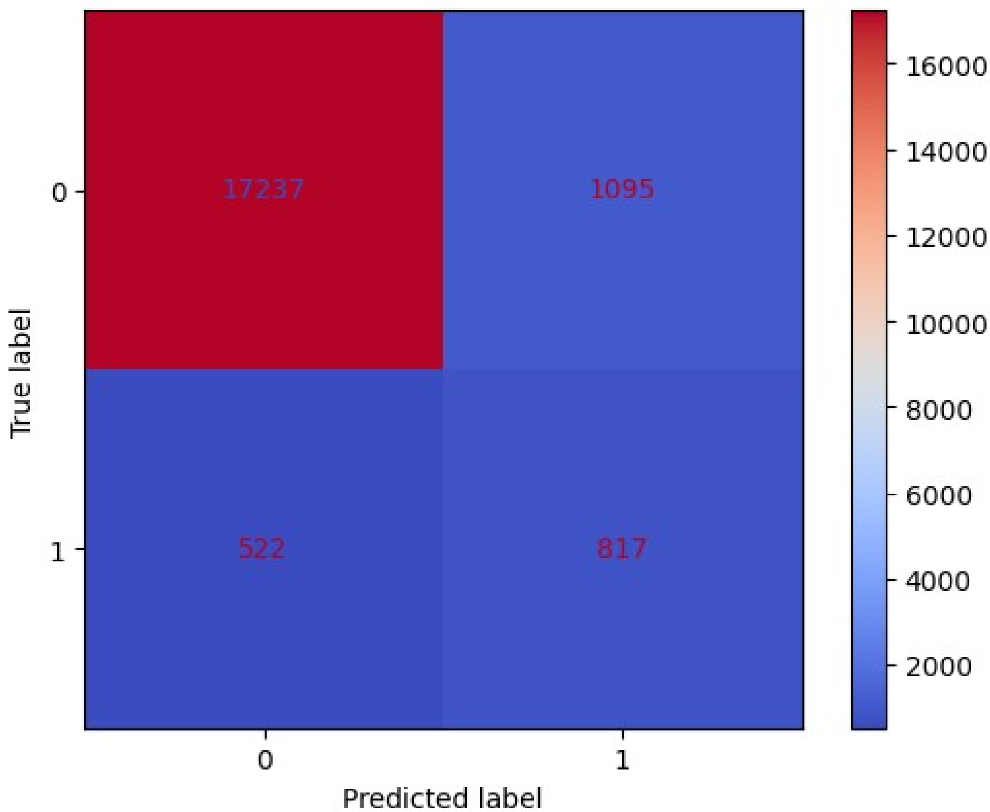
####**Balanced Accuracy**

```
calculate_accuracy(y_test, y_pred2_smote)
```

```
Accuracy=0.9178, Balanced Accuracy=0.7752
```

####**Confusion Matrix**

```
c_matrix(y_test, y_pred2_smote, knn_smote_pipe)

confusion matrix=


array([[17237,  1095],
       [  522,   817]])
```



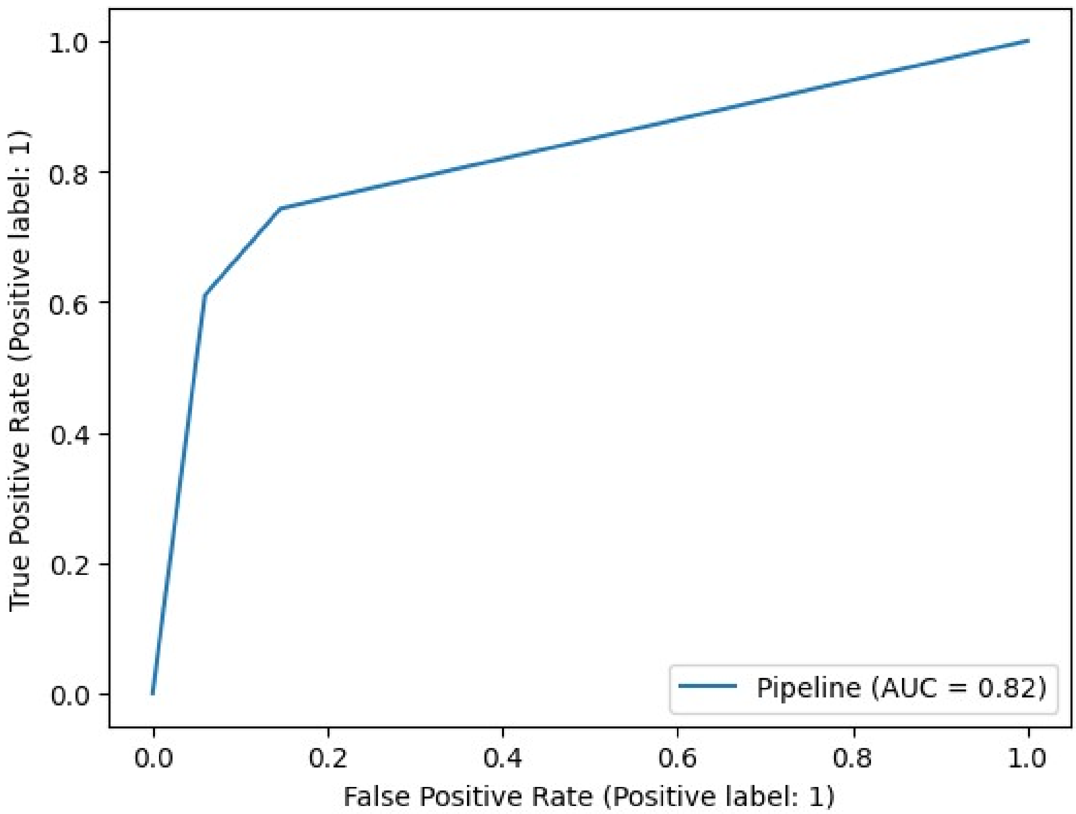
####**Classification Report**

```
class_report(y_test, y_pred2_smote)

classification report=
               precision    recall  f1-score   support

           0       0.97      0.94      0.96     18332
           1       0.43      0.61      0.50      1339

    accuracy                           0.92     19671
```

```
   macro avg       0.70      0.78      0.73     19671
weighted avg       0.93      0.92      0.92     19671
```

####**ROC Curve**

```
roc_curve(knn_smote_pipe, X_test, y_test)
```



####**Cost Matrix**

```
cost_matrix(knn_smote_pipe, X_train, y_train)

average cost for simple pipeline= 3960.8
```

###**7.6 Final Prediction**

```
y_pred2_smote2 = knn_smote_pipe.predict(X)
df1 = df.copy()
df1['predict_bankrupt'] = y_pred2_smote2
df1 # df1 = add the new prediction on the original dataset(df)

                   is_bankruptcy  Current assets  Cost of goods
sold  \
company_name year
```

```
C_1          1999               0        511.267            833.107
             2000               0        485.856            713.811
             2001               0        436.656            526.477
             2002               0        396.412            496.747
             2003               0        432.204            523.302
...                           ...            ...                ...
C_8971       2014               0        233.211             43.338
             2015               0        105.559             59.184
             2016               0         63.971             69.074
             2017               0        135.207             66.527
             2018               0         82.589             68.817

                   Depreciation and amortization   EBITDA
Inventory  \
company_name year
C_1          1999                         18.373   89.031    336.018
             2000                         18.577   64.367    320.590
             2001                         22.496   27.207    286.588
             2002                         27.172   30.745    259.954
             2003                         26.680   47.491    247.245
...                                          ...      ...        ...
C_8971       2014                         14.094   45.615      3.376
             2015                         42.592  202.133      2.288
             2016                         65.057   79.051      2.581
             2017                         65.330   69.171      2.013
             2018                         65.201   67.262      2.112

                   Net Income  Total Receivables  Market Value  Net
```

```
Sales  \
company_name year

C_1          1999      35.163                128.348      372.7519
1024.333
             2000      18.531                115.187      377.1180
874.255
             2001     -58.939                 77.528      364.5928
638.721
             2002     -12.410                 66.322      143.3295
606.337
             2003       3.504                104.661      308.9071
651.958
...                       ...                    ...           ...
...
C_8971       2014      25.261                 22.846      756.4827
104.223
             2015     129.688                 54.611      527.5750
291.153
             2016      -1.442                 42.467      578.8868
169.858
             2017     -20.401                 27.217      412.6241
161.884
             2018     -50.946                 45.839      354.1786
160.513

                   Total Assets  Total Long-term Debt      EBIT  Gross
Profit  \
company_name year

C_1          1999       740.998               180.447    70.658
191.226
             2000       701.854               179.987    45.790
160.444
             2001       710.199               217.699     4.711
112.244
             2002       686.621               164.658     3.573
109.590
             2003       709.292               248.666    20.811
128.656
...                         ...                   ...       ...
...
C_8971       2014      1099.101               184.666    31.521
60.885
             2015      1865.926               770.103   159.541
231.969
             2016      1746.235               683.985    13.994
100.784
             2017      1736.110               694.035     3.841
95.357
```

```
             2018      1625.370              632.122    2.061
91.696

                   Total Current Liabilities  Retained Earnings  \
company_name year
C_1          1999                    163.816            201.026
             2000                    125.392            204.065
             2001                    150.464            139.603
             2002                    203.575            124.106
             2003                    131.261            131.884
...                                      ...                ...
C_8971       2014                     28.197             28.095
             2015                     88.128            157.783
             2016                     85.765            156.341
             2017                     82.010            135.941
             2018                     79.365             84.995

                   Total Revenue  Total Liabilities  Total Operating
Expenses  \
company_name year

C_1          1999       1024.333            401.483
935.302
             2000        874.255            361.642
809.888
             2001        638.721            399.964
611.514
             2002        606.337            391.633
575.592
             2003        651.958            407.608
604.467
...                          ...                ...
...
C_8971       2014        104.223            225.887
58.608
             2015        291.153            880.327
89.020
             2016        169.858            770.233
90.807
             2017        161.884            776.697
92.713
             2018        160.513            712.687
93.251

                   predict_bankrupt
company_name year
C_1          1999                 0
             2000                 0
             2001                 0
             2002                 0
```

```
             2003                 0
...                             ...
C_8971       2014                 0
             2015                 0
             2016                 0
             2017                 0
             2018                 0

[78682 rows x 20 columns]
```

```
alivedf1 = df1[df1['predict_bankrupt']==0]
faileddf1 = df1[df1['predict_bankrupt']==1]
print('basic statistics about the alive company dataset (include =
"number"):')
display(alivedf1.describe(include = 'number'))
print('basic statistics about the failed company dataset (include =
"number"):')
display(faileddf1.describe(include = 'number'))
```

```
basic statistics about the alive company dataset (include = "number"):

       is_bankruptcy  Current assets  Cost of goods sold  \
count   72890.000000    72890.000000        72890.000000
mean        0.007175      919.641944         1655.249681
std         0.084403     4066.882328         9242.547560
min         0.000000       -7.760000         -366.645000
25%         0.000000       19.289250           17.151500
50%         0.000000      103.392500          104.322000
75%         0.000000      453.069000          658.140000
max         1.000000   169662.000000       374623.000000

       Depreciation and amortization        EBITDA     Inventory  \
count                   72890.000000  72890.000000  72890.000000
mean                      124.386420    396.495107    209.889237
std                       673.916692   2084.059773   1094.011669
min                         0.000000 -21913.000000      0.000000
25%                         1.188000     -0.610000      0.000000
50%                         7.971000     15.822000      7.205000
75%                        48.235750    145.798750     77.602500
max                     28430.000000  81730.000000  62567.000000

          Net Income  Total Receivables  Market Value      Net
Sales  \
count   72890.000000       72890.000000  7.289000e+04   72890.000000

mean      143.498819         299.481590  3.618874e+03    2461.642678

std      1303.855903        1382.600192  1.909718e+04   12370.953151

min    -98696.000000          -0.006000  1.000000e-04   -1964.999000
```

```
25%        -6.287000          3.420000  3.594120e+01      28.018750

50%         2.157000         23.626500  2.426296e+02     188.548500

75%        44.062750        137.067750  1.334322e+03    1092.605750

max    104821.000000      65812.000000  1.073391e+06  511729.000000


        Total Assets  Total Long-term Debt          EBIT   Gross
Profit  \
count   72890.000000          72890.000000  72890.000000
72890.000000
mean     2967.515471            733.204506    272.108542
806.393111
std     13337.404277           3318.835009   1547.672372
3910.838492
min         0.001000             -0.023000 -25913.000000  -
21536.000000
25%        37.859500              0.000000     -2.333750
8.915000
50%       216.136000              7.057500      7.360500
65.436000
75%      1207.959250            246.048000     93.300000
359.248000
max    531864.000000         166250.000000  71230.000000
137106.000000

       Total Current Liabilities  Retained Earnings  Total Revenue  \
count               72890.000000       72890.000000   72890.000000
mean                  632.273175         586.744846    2461.642678
std                  3032.882600        6596.012562   12370.953151
min                     0.001000     -102362.000000   -1964.999000
25%                     8.827250         -62.774750      28.018750
50%                    43.572000          -0.002500     188.548500
75%                   230.761250         161.432250    1092.605750
max                116866.000000      402089.000000  511729.000000

       Total Liabilities  Total Operating Expenses  predict_bankrupt
count       72890.000000              72890.000000           72890.0
mean         1818.429628               2065.147598               0.0
std          8286.054262              10782.557289               0.0
min             0.001000               -317.197000               0.0
25%            13.351000                 33.075000               0.0
50%            81.200000                171.355500               0.0
75%           637.286000                911.418500               0.0
max        337980.000000             481580.000000               0.0

basic statistics about the failed company dataset (include =
"number"):
```

	is_bankruptcy	Current assets	Cost of goods sold
count	5792.000000	5792.000000	5792.000000
mean	0.810946	386.046215	830.383940
std	0.391585	1119.295540	2785.079876
min	0.000000	0.001000	-0.666000
25%	1.000000	14.995500	15.802000
50%	1.000000	74.146000	96.707500
75%	1.000000	258.937000	444.781000
max	1.000000	16103.000000	40683.000000

	Depreciation and amortization	EBITDA	Inventory	Net Income
count	5792.000000	5792.000000	5792.000000	5792.000000
mean	81.565534	128.393766	97.360935	-48.266364
std	253.758486	518.106680	460.458992	573.049955
min	0.000000	-8218.500000	0.000000	-27446.000000
25%	1.239000	-5.013500	0.029250	-27.060000
50%	7.590000	5.929000	5.456000	-3.882000
75%	45.370250	79.491750	48.057000	8.092250
max	5475.000000	6136.000000	9963.000000	4504.000000

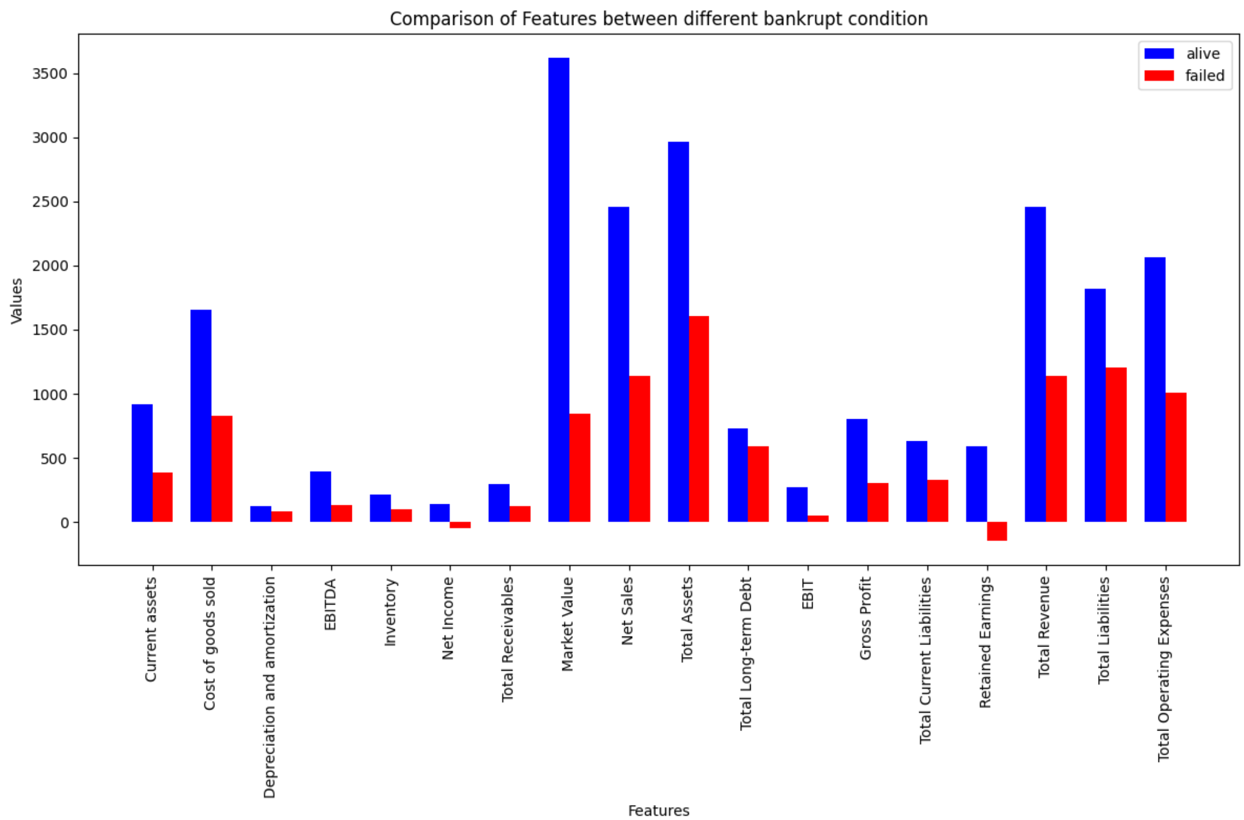
	Total Receivables	Market Value	Net Sales	Total Assets
count	5792.000000	5792.000000	5792.000000	5792.000000
mean	127.652074	840.555791	1135.473712	1603.555791
std	403.122021	3078.639202	3515.478844	5153.768371
min	0.000000	0.001300	-0.234000	0.005000
25%	2.139250	26.403475	21.116250	32.222000
50%	14.266000	118.443050	160.614000	183.981000
75%	78.459750	504.684350	678.461500	811.636000
max	6786.000000	139092.655000	53012.000000	76995.000000

	Total Long-term Debt	EBIT	Gross Profit
count	5792.000000	5792.000000	5792.000000
mean	587.566787	46.828232	305.089772
std	2040.308534	395.878152	921.392672
min	0.000000	-10537.000000	-8001.000000
25%	0.175750	-10.437250	4.256000
50%	16.480500	0.030000	42.845500
75%	278.401000	35.271750	217.737750
max	21586.000000	4822.000000	15192.000000

	Total Current Liabilities	Retained Earnings	Total Revenue

```
count         5792.000000        5792.000000    5792.000000
mean           330.682565        -150.597021    1135.473712
std           1203.856332        1746.390517    3515.478844
min              0.005000      -43091.000000      -0.234000
25%              9.554750        -139.146750      21.116250
50%             40.277500         -27.371500     160.614000
75%            154.569250          33.584750     678.461500
max          41695.000000        7832.000000   53012.000000

       Total Liabilities  Total Operating Expenses  predict_bankrupt
count        5792.000000               5792.000000            5792.0
mean         1208.947542               1007.079946               1.0
std          4091.377077               3270.758436               0.0
min             0.005000                 -0.016000               1.0
25%            15.373750                 30.450000               1.0
50%            90.822500                143.558500               1.0
75%           548.848000                580.510250               1.0
max         64092.000000              49363.000000               1.0
```

```
a = alivedf1.describe(include = 'number').iloc[1] # a dataset
represent the alive company info only display mean result
b = faileddf1.describe(include = 'number').iloc[1] # b dataset
represent the alive company info only display mean result
a.drop(['is_bankruptcy','predict_bankrupt'],inplace=True)
b.drop(['is_bankruptcy','predict_bankrupt'],inplace=True)

import matplotlib.pyplot as plt
import numpy as np


features = a.index
values_a = a.values
values_b = b.values

bar_width=0.35
index = np.arange(len(features))

plt.figure(figsize=(12, 8))
plt.bar(index, values_a , bar_width, label='alive',color = 'blue')
plt.bar(index + bar_width, values_b , bar_width, label='failed',color
= 'red')
plt.xlabel('Features')
plt.ylabel('Values')
plt.title('Comparison of Features between different bankrupt
condition')
plt.xticks(index + bar_width / 2, features, rotation='vertical')
plt.legend()
plt.tight_layout()

plt.show()
```



Insights

From financial metrics, the mean current assets for alive companies stand substantially higher than for failed companies, pointing to successful companies maintaining elevated levels of liquid assets, a contributing factor to their financial stability. In contrast, alive companies exhibit positive net income on average, whereas failed companies show a negative net income, underscoring the financial losses experienced by failed companies leading to bankruptcy.

Surprisingly, our anticipation regarding higher long-term debt and total liabilities for failed companies is contradicted. This suggests that successful companies may be more open to leveraging long-term financing for strategic growth or investments. Moreover, these successful companies adeptly manage financial obligations to sustain their operations. Operationally, alive companies boast higher EBITDA, indicative of robust cash flows from operational activities. However, they also incur higher operating expenses, hinting at the costs associated with maintaining successful operations.

From a market value perspective, alive companies exhibit substantially higher values compared to failed companies, signaling heightened investor confidence in the future potential and performance of successful companies. These insights drive our motivation throughout the project and hold importance for stakeholders, investors, and financial institutions seeking a nuanced understanding of the risks associated with companies' financial health and bankruptcy potential.

##8. Challenge

Given the highly imbalanced nature of our dataset, where approximately 97% of datapoints represent the "alive" class and only 3% represent the "failed" class, we implement several strategies for effective evaluation.

Firstly, in response to the challenge posed by imbalanced datasets, we prioritize balanced accuracy over traditional accuracy metrics when assessing our models. Traditional accuracy can be misleading in imbalanced scenarios as it tends to favor the majority class. Balanced accuracy, which considers the mean of sensitivity and specificity, offers a more reliable evaluation across all classes.

Secondly, in our model tuning, we incorporate the `class_weight='balanced'` hyperparameter to address the impact of imbalanced data. This adjustment ensures that the model assigns appropriate weights to different classes during training, giving emphasis to the minority class and enhancing predictive accuracy for both major and minor classes.

Thirdly, we employ resampling techniques, specifically over-sampling, to tackle the imbalance. This involves duplicating or generating synthetic samples for the minority class, providing the model with more instances to learn and distinguish patterns related to that class. This technique is crucial in preventing bias towards the majority class and fostering a more equitable model.

Fourthly, we also leverage the SMOTE (Synthetic Minority Over-sampling Technique) method to address the imbalanced problem. SMOTE helps by creating new data points for the smaller group, making the data more balanced. This way, the model can learn better from both groups and make fair predictions.

Lastly, K-fold cross-validation serves as an additional tool to address this problem. Specifically, K-fold cross-validation, when combined with these strategies, helps us navigate the challenges posed by imbalanced datasets.

Through these thoughtful approaches, our goal is to enhance the robustness and fairness of our machine learning models in the context of imbalanced datasets.

##**9. Conclusion**

In our comprehensive project journey, our primary objective was to craft a classification model that excels in balanced accuracy, particularly within the intricate landscape of a highly imbalanced dataset. Our exploration spanned various models, encompassing Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). Despite exhaustive efforts in training diverse models, the incremental gains in balanced accuracy were modest.

Beyond model selection, our focus extended to feature selection, delving into the nuanced impact of each variable on shaping the growth and success trajectories of the companies under scrutiny.

In summary, our project underscores the paramount importance of achieving peak accuracy in predictive modeling. The preference for KNN SMOTE signifies its adeptness in navigating imbalanced data challenges. Additionally, insights gained from feature selection illuminate how specific variables shape the growth dynamics of companies.

Further enriching our understanding is the recognition that stakeholders hold different perspectives on particular issues. For companies, a grasp of their financial health guides future plans, influencing decisions to earn more, spend judiciously, or seek external assistance. Simultaneously, investors keenly analyze a company's financial standing to make informed investment decisions, directing capital where growth potential is perceived. Predicting a company's trajectory, therefore, becomes pivotal for both business entities and investors alike, shaping strategic actions and investment choices. Ultimately, our work not only aids investors in making well-informed decisions but also empowers companies to navigate toward success with a nuanced understanding of their growth dynamics.