1. Importing Libraries

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
```

2. Load fataset

```
df = pd.read_csv("/content/archive.zip")
print(df)
```

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

       ROA(A) before interest and % after tax  \
0                                    0.424389
1                                    0.538214
2                                    0.499019
3                                    0.451265
4                                    0.538432
...                                       ...
6814                                 0.539468
6815                                 0.538269
6816                                 0.533744
6817                                 0.559911
6818                                 0.570105

       ROA(B) before interest and depreciation after tax  \
0                                               0.405750
1                                               0.516730
2                                               0.472295
3                                               0.457733
4                                               0.522298
...                                                  ...
6814                                            0.543230
6815                                            0.524172
6816                                            0.520638
6817                                            0.554045
6818                                            0.549548

       Operating Gross Margin   Realized Sales Gross Margin  \
0                    0.601457                      0.601457
1                    0.610235                      0.610235
2                    0.601450                      0.601364
3                    0.583541                      0.583541
4                    0.598783                      0.598783
...                       ...                           ...
6814                 0.604455                      0.604462
6815                 0.598308                      0.598308
6816                 0.610444                      0.610213
6817                 0.607850                      0.607850
6818                 0.627409                      0.627409

       Operating Profit Rate   Pre-tax net Interest Rate  \
0                   0.998969                    0.796887
1                   0.998946                    0.797380
2                   0.998857                    0.796403
3                   0.998700                    0.796967
4                   0.998973                    0.797366
```

3. Seperate feature and target

```
X = df.drop(columns=['Bankrupt?'])
y = df['Bankrupt?']
```

4. Standardize features

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

5. Train-test split (80/20)

```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)
```

6. Apply SMOTE to balance classes: We will apply smote to see if it gives us more accurate than random under sampling.

```
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

7. Check new class distribution

```
print("Before SMOTE:", y_train.value_counts())
print("After SMOTE:", y_train_smote.value_counts())
```

```
Before SMOTE: Bankrupt?
0    5279
1     176
Name: count, dtype: int64
After SMOTE: Bankrupt?
0    5279
1    5279
Name: count, dtype: int64
```

After applying smote class distribution is balanced.

Model training

1. Logistic Regression (Baseline Model)

1. Insert libraries

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix
```

2. Initialize and train model

```
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train_smote, y_train_smote)
```

```
LogisticRegression
LogisticRegression(max_iter=1000)
```

3. Predictions

```
y_pred_lr = log_reg.predict(X_test)
y_prob_lr = log_reg.predict_proba(X_test)[:, 1]
```

4. Evaluation

```
print("Logistic Regression Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
print("Precision:", precision_score(y_test, y_pred_lr))
print("Recall:", recall_score(y_test, y_pred_lr))
print("F1 Score:", f1_score(y_test, y_pred_lr))
print("AUC-ROC:", roc_auc_score(y_test, y_prob_lr))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr))
```

```
Logistic Regression Performance:
Accuracy: 0.8922287390029325
Precision: 0.2023121387283237
Recall: 0.7954545454545454
F1 Score: 0.3225806451612903
AUC-ROC: 0.9147727272727273
Confusion Matrix:
 [[1182  138]
 [   9   35]]
```

2. Random Forest (Non-linear Model)

1. Importing Libraries

```
from sklearn.ensemble import RandomForestClassifier
```

2. Initialize and train model

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train_smote, y_train_smote)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

3. Predictions

```
y_pred_rf = rf.predict(X_test)
y_prob_rf = rf.predict_proba(X_test)[:, 1]
```

4. Evaluation

```
print("Random Forest Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Precision:", precision_score(y_test, y_pred_rf))
print("Recall:", recall_score(y_test, y_pred_rf))
print("F1 Score:", f1_score(y_test, y_pred_rf))
print("AUC-ROC:", roc_auc_score(y_test, y_prob_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
```

```
Random Forest Performance:
Accuracy: 0.9618768328445748
Precision: 0.43548387096774194
Recall: 0.6136363636363636
F1 Score: 0.5094339622641509
AUC-ROC: 0.9373880853994491
Confusion Matrix:
 [[1285   35]
 [  17   27]]
```

3. XGBoost (Gradient Boosted Model)

1. Importing libraries

```
from xgboost import XGBClassifier
```

2. Initialize and train model

```
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_smote, y_train_smote)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning: [11:57:22] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
```

3. Predictions

```
y_pred_xgb = xgb.predict(X_test)
y_prob_xgb = xgb.predict_proba(X_test)[:, 1]
```

4.Evaluation

```
print("XGBoost Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("Precision:", precision_score(y_test, y_pred_xgb))
print("Recall:", recall_score(y_test, y_pred_xgb))
print("F1 Score:", f1_score(y_test, y_pred_xgb))
print("AUC-ROC:", roc_auc_score(y_test, y_prob_xgb))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
```

```
XGBoost Performance:
Accuracy: 0.966275659824047
Precision: 0.4791666666666667
Recall: 0.5227272727272727
F1 Score: 0.5
AUC-ROC: 0.9491219008264463
Confusion Matrix:
 [[1295   25]
 [  21   23]]
```

4. **Roc Curves for better understanding**

1. Importing libraries

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
```

2. Calculate ROC curve values

```
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_prob_lr)
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_prob_rf)
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_prob_xgb)
```

3. Calculate AUC

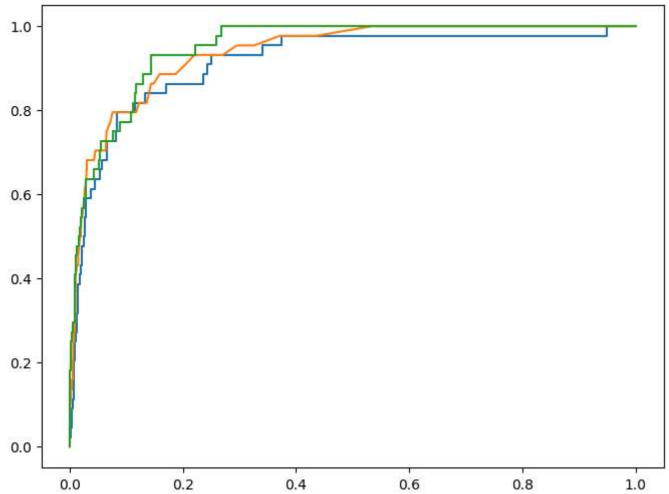
```
auc_lr = auc(fpr_lr, tpr_lr)
auc_rf = auc(fpr_rf, tpr_rf)
auc_xgb = auc(fpr_xgb, tpr_xgb)
```

4. Plot ROC curves

```
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {auc_lr:.2f})')
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {auc_rf:.2f})')
```

```
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost (AUC = {auc_xgb:.2f})')
```

```
[<matplotlib.lines.Line2D at 0x7c3cdb119ad0>]
```

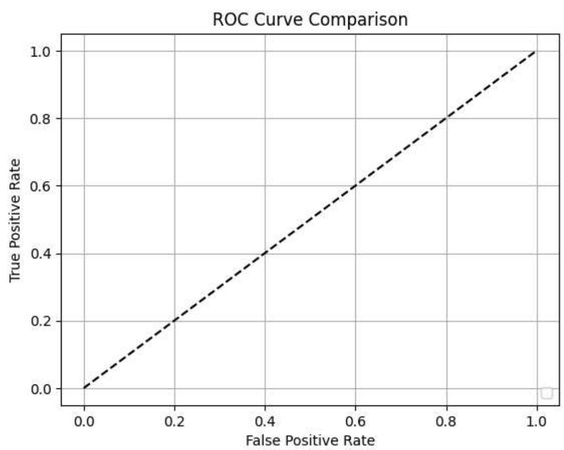


5. Random guessing line

```
plt.plot([0, 1], [0, 1], 'k--')

plt.title('ROC Curve Comparison')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```

```
/tmp/ipython-input-157065711.py:6: UserWarning: No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend() is call
  plt.legend(loc='lower right')
```



5. Feature importance analysis

A. Random Forest

1. Importing libraries

```
import pandas as pd
import numpy as np
```

2. Get feature importances from Random Forest

```
rf_importances = rf.feature_importances_
```

3. Create a dataframe for better visualization

```
rf_feature_importance = pd.DataFrame({
    'Feature': df.drop(columns=['Bankrupt?']).columns,
    'Importance': rf_importances
}).sort_values(by='Importance', ascending=False)

print(rf_feature_importance.head(10))
```

```
                                  Feature  Importance
39                    Borrowing dependency    0.083886
90                     Liability to Equity    0.051615
```

```
85              Net Income to Total Assets    0.050565
36                            Debt ratio %    0.042066
18  Persistent EPS in the Last Four Seasons    0.041178
9      Continuous interest rate (after tax)    0.040066
7               After-tax net Interest Rate    0.038034
89       Net Income to Stockholder's Equity    0.033305
37                         Net worth/Assets    0.032316
67         Retained Earnings to Total Assets    0.028188
```

B. XGBoost

1. Get feature importances from XGBoost

```
xgb_importances = xgb.feature_importances_
```

2. Create a dataframe

```
xgb_feature_importance = pd.DataFrame({
    'Feature': df.drop(columns=['Bankrupt?']).columns,
    'Importance': xgb_importances
}).sort_values(by='Importance', ascending=False)

print(xgb_feature_importance.head(10))
```

```
                                          Feature  Importance
39                            Borrowing dependency    0.233128
18          Persistent EPS in the Last Four Seasons    0.080226
9              Continuous interest rate (after tax)    0.068055
85                       Net Income to Total Assets    0.042599
8        Non-industry income and expenditure/revenue    0.028331
0    ROA(C) before interest and depreciation befor...    0.024962
20                        Revenue Per Share (Yuan ¥)    0.022371
91                  Degree of Financial Leverage (DFL)    0.020703
35                        Total debt/Total net worth    0.019371
45                      Accounts Receivable Turnover    0.015881
```

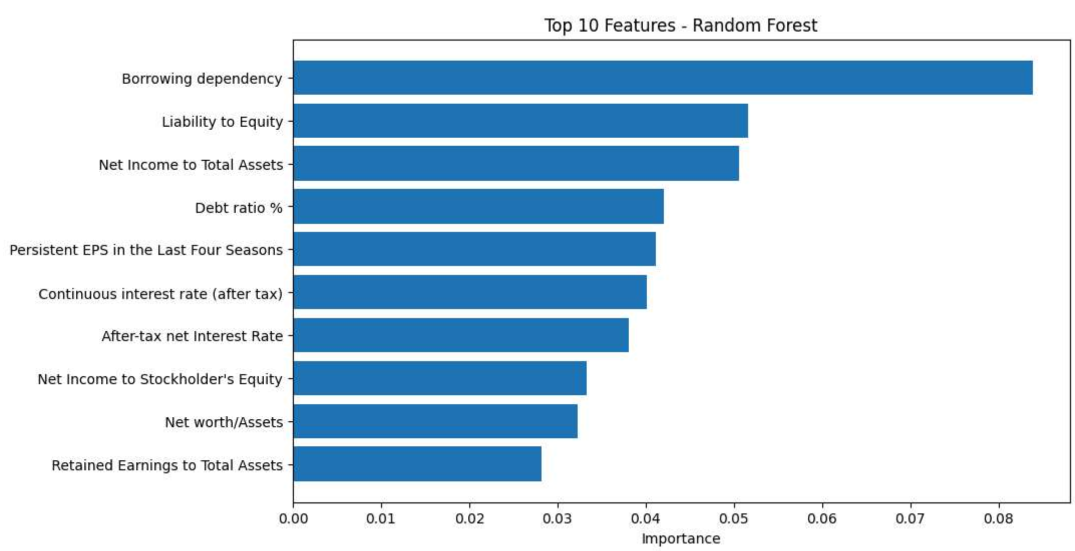
3. Plotting Feature Importance (Bar Chart)

1. Importing Libraries

```
import matplotlib.pyplot as plt
```

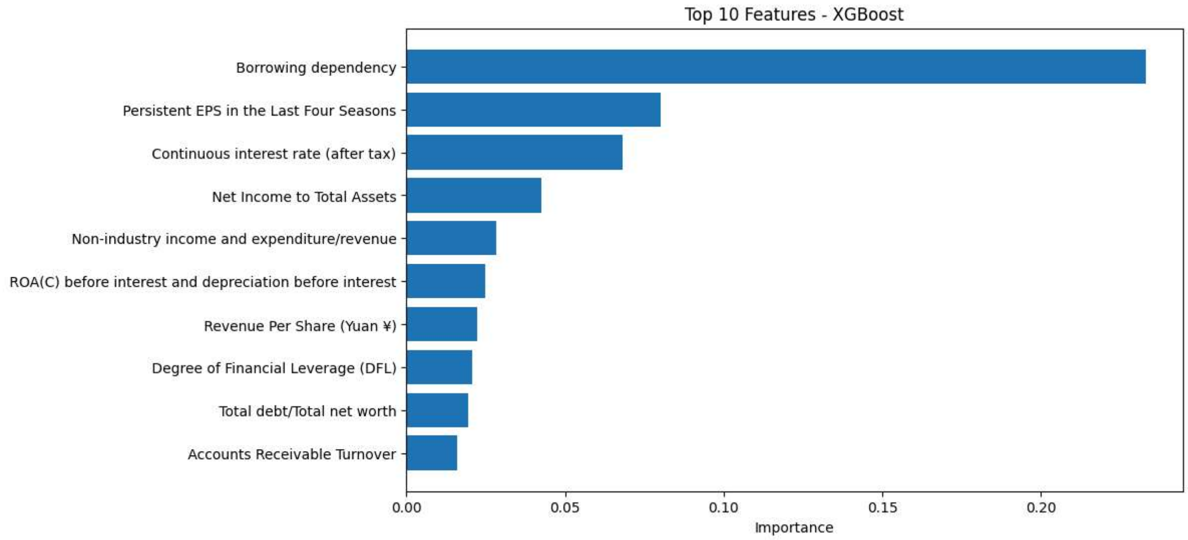
2. Plot Random Forest

```
plt.figure(figsize=(10, 6))
plt.barh(rf_feature_importance['Feature'][:10], rf_feature_importance['Importance'][:10])
plt.gca().invert_yaxis()
plt.title('Top 10 Features - Random Forest')
plt.xlabel('Importance')
plt.show()
```



3. Plot XGBoost

```
plt.figure(figsize=(10, 6))
plt.barh(xgb_feature_importance['Feature'][:10], xgb_feature_importance['Importance'][:10])
plt.gca().invert_yaxis()
plt.title('Top 10 Features - XGBoost')
plt.xlabel('Importance')
plt.show()
```



The model highlights liquidity and leverage ratios as the strongest predictors of financial distress.