Business Case: Machine Learning Model on SME's Loan Admission

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Model Selection

1. Introduction

In this project, the main objective is to develop models that can effectively predict whether to grant loans to small to medium-sized enterprises (SMEs) using supervised machine learning techniques. By utilizing these models, lenders can make informed decisions regarding loan approvals, mitigating the risk of default and optimizing their lending portfolios.

1.1 Data Set

The dataset utilized in this project is obtained from internal data sources, incorporating fields from both the income statement and balance sheet. It offers a comprehensive view of the financial status of small and medium-sized enterprises (SMEs). It comprises 36 features that capture essential financial information, including fields like Inventories, Receivables, Net Income and more.

1.2 Model Selection

The project will explore various supervised machine learning algorithms to train and evaluate the dataset.The following machine learning models will be employed to train and assess the dataset:

1. Decision Tree
2. Logistic Regression
3. Random Forest
4. Support Vector Machine
5. K Nearest Neighbor

In [24]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn import ensemble
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import recall_score, accuracy_score
from sklearn.metrics import plot_roc_curve



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

2. Data Preperation

2.1 Test Set

In [2]:
```
####X_test####
url = "/Users/hsingfentsai/Documents/Fenny/Job Search/Interview Prep/Validus/'
df_test = pd.read_excel(url, sheet_name=None)
sheet_names = df_test.keys()
```

In [3]:
```
PL_list = []
BS_list = []
for each in sheet_names:
    if 'PL' in each:
        PL_list.append(each)
    else:
        BS_list.append(each)
```

In [4]:
```
PL_df = pd.DataFrame()
for each in PL_list:
    df = pd.read_excel(url, sheet_name=each, header=None)
    df = df.T
    df.columns = df.iloc[0]
    df = df[1:]
    df.insert(4,'COGS', df.iloc[0,4:6].sum())
    df.insert(5,'Gross Profit', df['Revenue'] - df['COGS'])
    df.insert(9,'Total salary and expense',df.iloc[0,9:12].sum())
    df.drop(df.columns[[6,7,10,11,12]], axis=1, inplace=True)
    PL_df = pd.concat([PL_df,df], axis=0)
PL_df = PL_df.reset_index(drop=True)
```

In [5]:

```
BS_df = pd.DataFrame()
for each in BS_list:
    df = pd.read_excel(url, sheet_name=each, header=None)
    df = df.T
    df.columns = df.iloc[0]
    df = df[1:].reset_index(drop=True)
    df.insert(7,'Total Asset', df.iloc[0,4:7].sum())
    BS_df = pd.concat([BS_df,df], axis=0)
BS_df = BS_df.reset_index(drop=True)
```

In [6]:

```
X_test = pd.merge(PL_df, BS_df, on='UEN')
X_test.shape
```

Out[6]:

```
(18, 33)
```

In [7]:

```
# Get the UEN numbers does not exist in BS_df
uu = PL_df[~PL_df['UEN'].isin(BS_df['UEN'])].iloc[0,0]
print('STAM\'s UEN No. that did not provide BS file data : ' + uu)
```

```
STAM's UEN No. that did not provide BS file data : 200010036F
```

In [8]:

```
###Y_test###
url = "/Users/hsingfentsai/Documents/Fenny/Job Search/Interview Prep/Validus/
y_test = pd.read_csv(url)
Y_test = pd.merge(X_test, y_test, on='UEN')
Y_test = Y_test.iloc[:,[-1]]
Y_test.shape
```

Out[8]:

```
(18, 1)
```

In [9]:

```
X_test.rename(columns=lambda x: 'Y1_' + x, inplace=True)
X_test = X_test.iloc[:,1:]
X_test
```

Out[9]:

	Y1_Revenue	Y1_Sales	Y1_other Rev	Y1_COGS	Y1_Gross Profit	Y1_total other Income	Y1_Total salary and expense
0	720000	720000	0	6.229434e+05	97056.56	23413.2	0.000000e+00
1	1360000	1360000	0	8.166864e+05	543313.6	4168.8	2.817360e+05
2	3440000	3440000	0	6.546330e+05	2785367.0	416596.8	5.861406e+05
3	30990000	30990000	0	6.707259e+06	24282741.0	-115493.4	1.114809e+07
4	13950000	13950000	0	4.125201e+06	9824798.832	0	1.533183e+06
5	2300000	2300000	0	1.496164e+06	803835.812	19248.271	2.311458e+05
6	670000	670000	0	2.167695e+05	453230.5	0	8.417250e+04

	Y1_Revenue	Y1_Sales	Y1_other Rev	Y1_COGS	Y1_Gross Profit	Y1_total other Income	Y1_Total salary and expense
7	7630000	7630000	3200400	2.594900e+06	5035100	0	1.848000e+06
8	16306093	16306093	0	4.471506e+06	11834587.0	-104994	7.962924e+06
9	4232086	4232086	0	1.976513e+06	2255573.0	6522	8.349040e+05
10	15649573	15649573	0	1.442754e+07	1222037.0	182062	5.010340e+05
11	9772000	9772000	4040000	5.733000e+06	4039000	3851000	1.468000e+06
12	49950000	49950000	44900000	5.050000e+06	44900000	725000	7.330000e+05
13	5252000	5252000	2855000	2.397000e+06	2855000	NaN	2.000000e+06
14	12461000	12461000	9466000	2.996000e+06	9465000	1102000	7.100000e+05
15	46573000	46541000	47319000	0.000000e+00	46573000	1283000	7.760000e+05
16	2020000	2020000	1655000	3.660000e+05	1654000	96000	1.510000e+05
17	6930000	6930000	4572000	2.359000e+06	4571000	NaN	1.680000e+06

18 rows × 32 columns

In [10]:

```
#deal with NaN values, use mean to replace
na_list = (X_test.isna().sum()).to_list()
for i in range(len(na_list)):
    if na_list[i] > 0:
        mean = X_test[X_test.columns[i]].mean()
        X_test[X_test.columns[i]].fillna(mean, inplace=True)
```

In [11]:

```
#change data type to float
for i in range(X_test.shape[1]):
    X_test[X_test.columns[i]] = pd.to_numeric(X_test[X_test.columns[i]], erro
    X_test[X_test.columns[i]] = X_test[X_test.columns[i]].astype(float)
```

In [12]:

```
# list = []
# for each in X_test.columns:
#     if (X_test[each]<0).any():
#         if each not in list:
#             list.append(each)

# for each in list:
#     X_test.loc[X_test[each]<0, each]*= -1
```

2.2 Train Set

In [13]:

```
#read file
train_url = "/Users/hsingfentsai/Documents/Fenny/Job Search/Interview Prep/Va
df_train = pd.read_excel(train_url, sheet_name='Raw_data')
df_train
```

Out[13]:

	Application Date	UEN	Label	Financial as of	Y1_Revenue	Y1_Sales	Y1_other Rev	Y1_CO
0	2018-11-13	200375496X	0	2018-11-11	2860000.0	2860000.0	0.0	27414.
1	2018-11-27	201858669V	0	2018-10-28	1230000.0	1230000.0	0.0	394125.
2	2018-11-22	201473872D	0	2018-10-28	4730000.0	4730000.0	2284000.0	1917600.
3	2018-11-24	201312946M	1	2018-10-21	3167178.0	3167178.0	0.0	473822.
4	2018-10-18	200918909H	0	2018-10-16	1490207.0	1490207.0	0.0	927320.
...	...	...	...	...	...	...	...	
225	2018-12-09	201817341G	0	2017-03-01	7340000.0	7340000.0	0.0	4685329.
226	2018-11-27	201858669V	0	2017-02-11	1230000.0	1230000.0	0.0	394125.
227	2018-11-27	201858669V	0	2017-02-11	1230000.0	1230000.0	0.0	394125.
228	2018-02-03	201754368V	0	2017-01-04	1210000.0	1210000.0	0.0	256956.
229	2018-02-03	201754368V	0	2017-01-04	1210000.0	1210000.0	0.0	256956.

230 rows × 36 columns

2.2.1 Data Cleaning

1. Remove Outdated Data
2. Remove Duplicate data

In [14]:

```
df_train = df_train[~(df_train['Financial as of'] < '2018-01-01')]
df_train.drop_duplicates(subset='UEN', inplace=True)
df_train.shape
```

Out[14]:

```
(173, 36)
```

In [15]:

```
###Y_train###
Y_train = df_train.iloc[:,[2]]
Y_train.shape
```

Out[15]:

```
(173, 1)
```

In [16]:

```
df_train.drop(df_train.columns[[0, 1, 3]], axis=1, inplace=True)
X_train = df_train.iloc[:,1:]
Y_train = df_train.iloc[:,[0]]
X_train.shape
```

Out[16]:
```
(173, 32)
```

In [17]:
```
#change data type to float
X_train['Y1_Total Selling and Distribution expense'] = pd.to_numeric(X_train[
X_train['Y1_Total Selling and Distribution expense'] = X_train['Y1_Total Sell
```

In [18]:
```
#deal with NaN values, use mean to replace
na_list = (X_train.isna().sum()).tolist()
for i in range(len(na_list)):
    if na_list[i] > 0:
        mean = X_train[X_train.columns[i]].mean()
        X_train[X_train.columns[i]].fillna(mean, inplace=True)
```

2.2.2 Data Normalization

In [19]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train[X_train.columns] = scaler.fit_transform(X_train[X_train.columns])
X_test[X_test.columns] = scaler.fit_transform(X_test[X_test.columns])
```

2.2.3 Data Oversampling

In [20]:
```
Y_train.value_counts()
```

Out[20]:
```
Label
0        151
1         22
dtype: int64
```

1. RandomOverSampler

In [21]:
```
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler()
x_ros, y_ros = ros.fit_resample(X_train, Y_train)
y_ros.value_counts()
```

Out[21]:
```
Label
0        151
1        151
dtype: int64
```

1. SMOTE

In [28]:
```
from imblearn.over_sampling import SMOTE
X_smote,Y_smote = SMOTE(random_state=1).fit_resample(X_train, Y_train)
Y_smote.value_counts()
```

Out[28]:
```
Label
0        151
1        151
dtype: int64
```

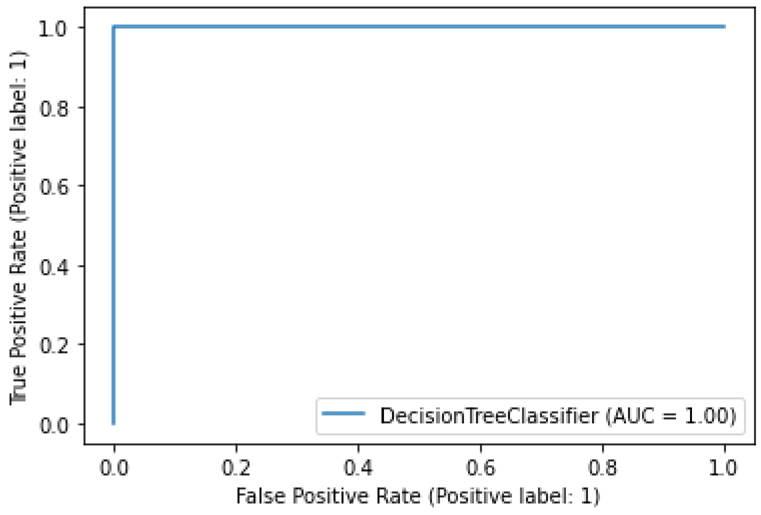
3. Data Modelling

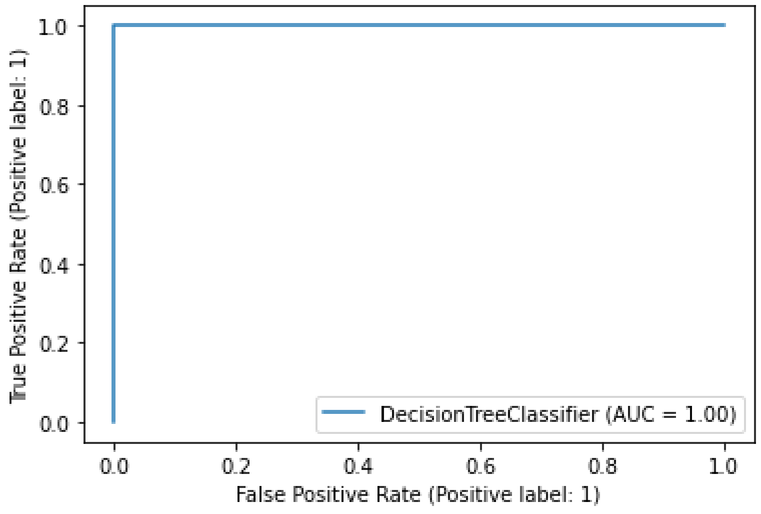
1. Decision Tree

In [36]:

```
from sklearn.tree import DecisionTreeClassifier

#Random Over Sampling
dt = DecisionTreeClassifier()
dt.fit(x_ros, y_ros)
pred = dt.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('ROS')
print('Recall Rate:', recall)
print("Accuracy:", accuracy , '\n')
plot_roc_curve(dt, x_ros, y_ros);

#SMOTE
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_smote, Y_smote)
pred = dt.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('SMOTE')
print('Recall Rate:', recall)
print("Accuracy:", accuracy)
plot_roc_curve(dt, X_smote, Y_smote);
```

```
ROS
Recall Rate: 0.0
Accuracy: 0.6666666666666666

SMOTE
Recall Rate: 0.0
Accuracy: 0.6666666666666666
```

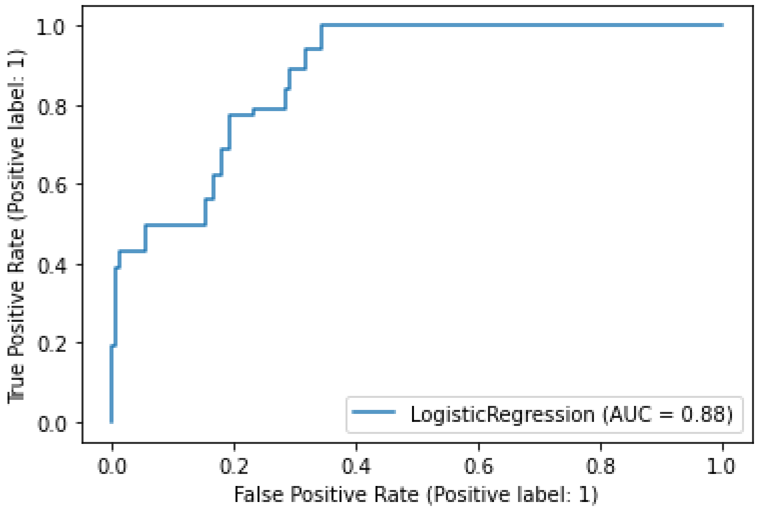


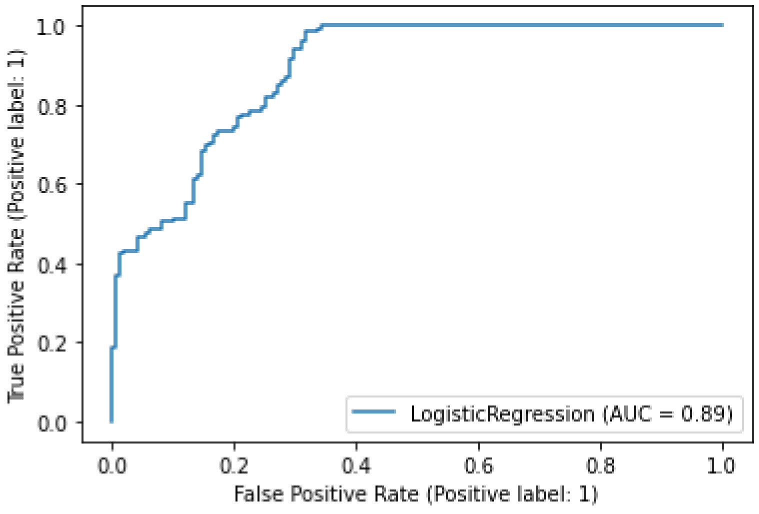


1. Logistic Regression

In [30]:
```
from sklearn import linear_model

#Random Over Sampling
model = linear_model.LogisticRegression(random_state=1)
model.fit(x_ros,y_ros)
pred = model.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('ROS')
print('Recall Rate:', recall)
print("Accuracy:", accuracy , '\n')
plot_roc_curve(model, x_ros, y_ros);

#SMOTE
model = linear_model.LogisticRegression(random_state=1)
model.fit(X_smote, Y_smote)
pred = model.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('SMOTE')
print('Recall Rate:', recall)
print("Accuracy:", accuracy)
plot_roc_curve(model, X_smote, Y_smote);
```

```
ROS
Recall Rate: 0.5
Accuracy: 0.6111111111111112

SMOTE
Recall Rate: 0.6666666666666666
Accuracy: 0.6666666666666666
```

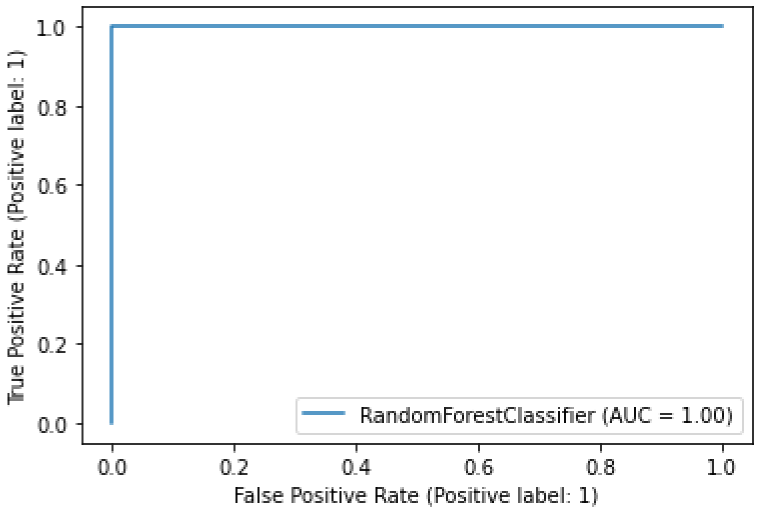


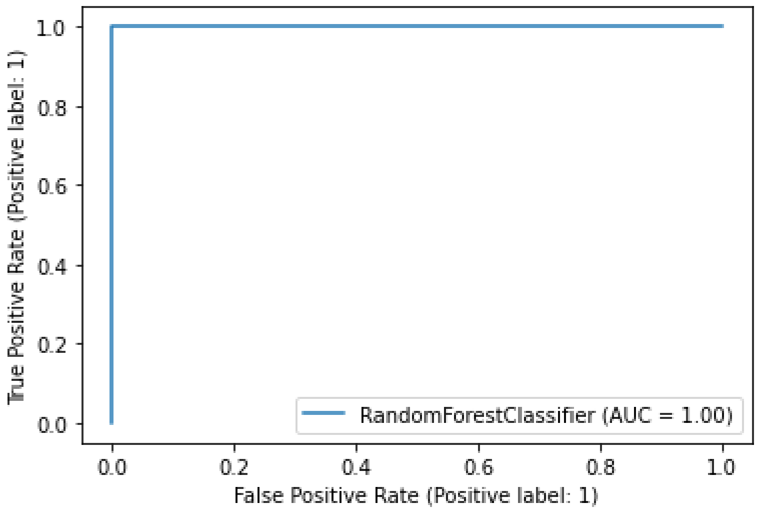


1. Random Forest

In [31]:
```
from sklearn import ensemble

#Random Over Sampling
model = ensemble.RandomForestClassifier(n_estimators=100,random_state=1)
model.fit(x_ros,y_ros)
pred = model.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('ROS')
print('Recall Rate:', recall)
print("Accuracy:", accuracy , '\n')
plot_roc_curve(model, x_ros, y_ros);

#SMOTE
model = ensemble.RandomForestClassifier(random_state=1)
model.fit(X_smote,Y_smote)
pred = model.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('SMOTE')
print('Recall Rate:', recall)
print("Accuracy:", accuracy)
plot_roc_curve(model, X_smote, Y_smote);
```

```
ROS
Recall Rate: 0.0
Accuracy: 0.6666666666666666

SMOTE
Recall Rate: 0.0
Accuracy: 0.6666666666666666
```





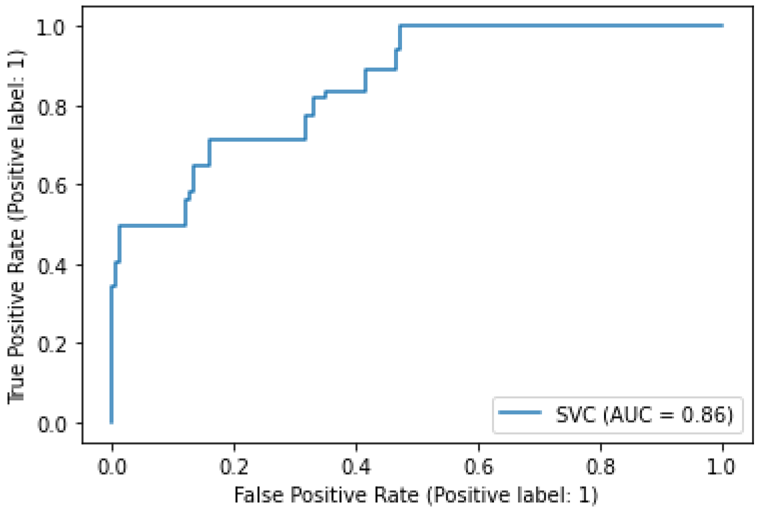
1. Support Vector Machine

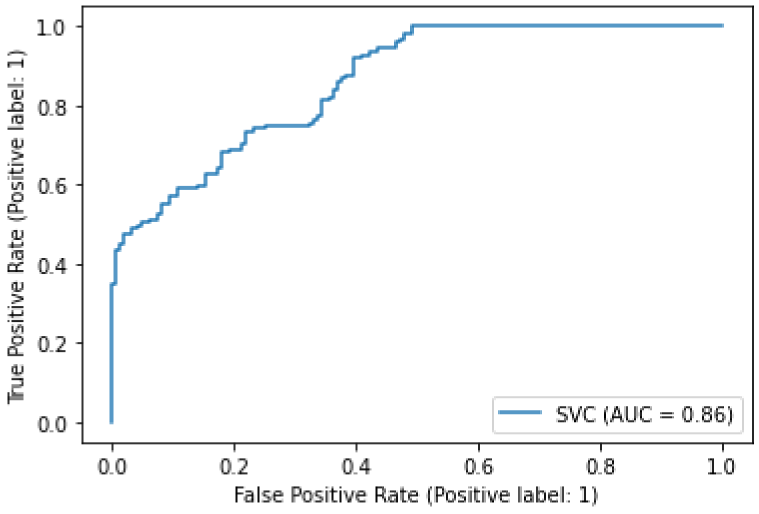
In [33]:

```
from sklearn.svm import SVC
#Random Over Sampling
svm = SVC()
svm.fit(x_ros, y_ros)
pred = svm.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('ROS')
print('Recall Rate:', recall)
print("Accuracy:", accuracy , '\n')
plot_roc_curve(svm, x_ros, y_ros);

from sklearn.svm import SVC
svm = SVC()
svm.fit(X_smote, Y_smote)
pred = svm.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)
```

```
print('SMOTE')
print('Recall Rate:', recall)
print("Accuracy:", accuracy)
plot_roc_curve(svm, X_smote, Y_smote);
```

```
ROS
Recall Rate: 0.6666666666666666
Accuracy: 0.6111111111111112

SMOTE
Recall Rate: 0.8333333333333334
Accuracy: 0.6666666666666666
```





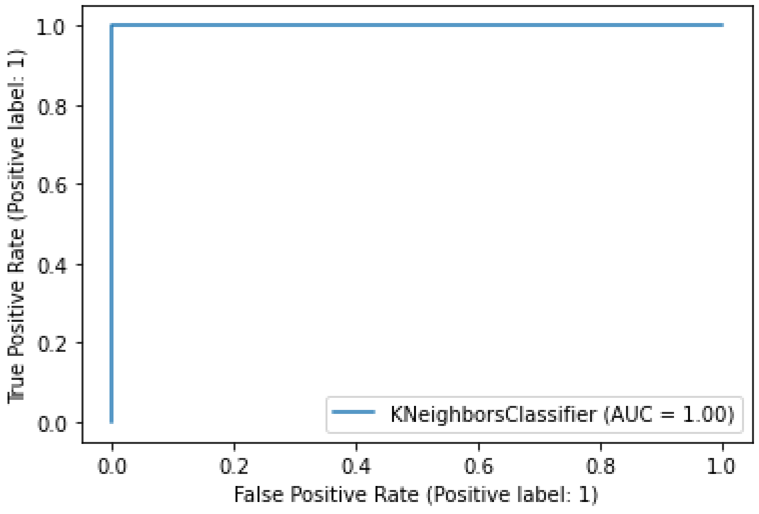
1. K Nearest Neighbors

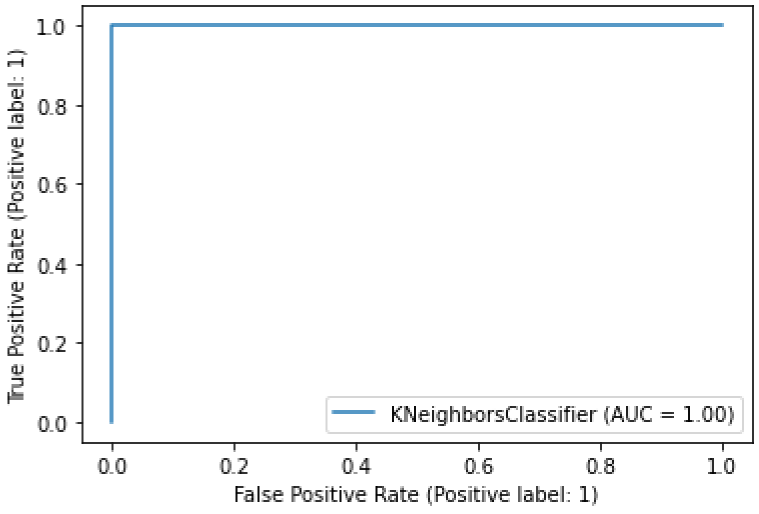
In [34]:

```
from sklearn.neighbors import KNeighborsClassifier
#Random Over Sampling
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_ros, y_ros)
pred = knn.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('ROS')
print('Recall Rate:', recall)
print("Accuracy:", accuracy , '\n')
plot_roc_curve(knn, x_ros, y_ros);

#SMOTE
knn = KNeighborsClassifier(n_neighbors=3)
```

```
knn.fit(X_smote, Y_smote)
pred = knn.predict(X_test)
recall = recall_score(Y_test, pred)
accuracy = accuracy_score(Y_test, pred)

print('SMOTE')
print('Recall Rate:', recall)
print("Accuracy:", accuracy)
plot_roc_curve(knn, X_smote, Y_smote);
```

```
ROS
Recall Rate: 0.16666666666666666
Accuracy: 0.6111111111111112

SMOTE
Recall Rate: 0.5
Accuracy: 0.7222222222222222
```





Improve Model - SVM

In [35]:
```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import recall_score, accuracy_score
param_grid = {
    'C': [0.1, 1, 10],
    'gamma': [0.1, 0.01, 0.001]
}
svm = SVC()

grid_search = GridSearchCV(svm, param_grid, cv=5)
grid_search.fit(X_smote, Y_smote)
```

```
best_params = grid_search.best_params_
best_estimator = grid_search.best_estimator_

pred = best_estimator.predict(X_test)
recall = recall_score(Y_test, pred)

print("Best Parameters:", best_params)
print("Recall:", recall)
cm = confusion_matrix(Y_test,pred)
print("accuracy", (cm[0,0]+cm[1,1])/(sum(sum(cm))))
```

```
Best Parameters: {'C': 10, 'gamma': 0.1}
Recall: 0.3333333333333333
accuracy 0.7222222222222222
```

4. Conclusion

- Random Over Sampling | | Accuracy | Recall Rate | | --------- | -------- | -------- | | Decision Tree | 0.67 | 0.0 | | Logistic Regression | 0.61 | 0.5 | | Random Forest | 0.67 | 0.0 | | Support Vector Machine| 0.61 | 0.67 | | K Nearest Neighbor | 0.61 | 0.16 |
- SMOTE | | Accuracy | Recall Rate | | --------- | -------- | -------- | | Decision Tree | 0.67 | 0.0 | | Logistic Regression | 0.67 | 0.67 | | Random Forest | 0.67 | 0.0 | | **Support Vector Machine| 0.67 | 0.83 | | K Nearest Neighbor | 0.72 | 0.5 |**

In this task, the main objective is to assess whether an SME (Small and Medium Enterprise) is good or bad in order to minimize the probability of default in the future, should a loan be granted to them.

Therefore, our focus lies on reducing Type 2 Error, also known as False Negatives. A False Negative occurs when the model incorrectly predicts a company as good when, in reality, it is a bad company. Preventing this error is crucial because if we mistakenly categorize a bad company as good, there is a risk of providing a loan that may not be repaid on time or at all.

To address this concern, we aim to achieve a higher Recall Rate. The recall rate, often referred to as sensitivity or true positive rate, is a performance metric that quantifies the proportion of actual bad companies correctly identified as bad by the model. A higher recall rate signifies that the model is better at capturing the bad companies, thus reducing the number of False Negatives.

By striving for a higher recall rate, we prioritize the accurate identification of bad companies, reducing the risk of lending to entities that are more likely to default. This approach enhances the overall performance of the model by minimizing the chances of extending loans to companies with a higher probability of failing to repay the loan.

To conclude, we will choose the Support Vector Machine (SVM) model with 'SMOTE' oversampling as our final selection since it achieves the highest 'Recall Rate' compared to all other models.

5. Improvement

Although the SVM model currently achieves a Recall Rate of 0.83 and a Accuracy of 0.67, there are steps we can take to further enhance its performance. One key approach is to acquire additional data, as doing so has the potential to improve the model's ability to generalize and capture the underlying patterns in the dataset.

Currently, our model is based on a dataset that includes only 173 rows of data after thorough cleaning, which involved removing outdated and duplicate entries. To expand the dataset and enhance the model's performance, we should consider gathering more relevant data points. This can be achieved by reaching out to additional sources or collecting data over an extended period of time.

By increasing the size and diversity of our dataset, we provide the model with a broader range of examples to learn from. This can help it better understand the underlying patterns and relationships within the data, leading to improved predictive performance.

Therefore, by actively seeking out more relevant data points and expanding our dataset, we can increase the chances of achieving even better performance with the SVM model and further enhance its ability to accurately predict and classify SMEs.

6. Business Suggestion

6.1 Assess SME using Model + Financial Ratio

To better maximize our company business, we should collaborate with those 'good' company who pay the loan in time. So that our business funds can run longer in the future.

To achieve this, we can use the model we created above to first better filter out the bad company, and from these good company, we can then use other rating indicators such as "Liquidity Ratio" and "Solvency Ratio" to identify and measure the loan quialification of a particular SME.

- **Following are the some common type of Liquidity Ratio that we can take into consideration for a company's ability to pay off its short-term liabilities:**

1. **Current Ratio: Current Assets / Current Liabilities**
2. **Quick Ratio: (Current Asset-Inventories-Prepaid Expenses)/ Current Liabilities**
3. **Cash Ratio: Cash and equivalent / Current liabilities**

- **Following are the some common type of Solvency Ratio that we can take into consideration to assess a company's long-term financial obligations - the repayment of debt principal and interest expense ability:**

1. Solvency Ratio: (Net Income + Depreciation) / All Liabilities (Short-term + Long-term Liabilities)
2. Debt-to-Equity Ratio: Total debt / Total Assets
3. Debt-to-Asset Ratio: Total Shareholder's Equity / Total Assets

Take Current Ratio as an example.

In general, it is commonly believed that a Current ratio greater than 2 is considered favorable, indicating a better short-term solvency ability. If the Current ratio is too low, it suggests poor short-term debt repayment capacity. On the other hand, if the ratio is too high, it indicates low efficiency in utilizing company funds.

It is important to consider the Current ratio in conjunction with the amount of accounts receivable and the inventory turnover rate to better assess the company's solvency.

Take Debt-to-Equity Ratio as another example.

A higher Debt to Equity Ratio indicates a higher level of debt relative to equity, suggesting that the company relies more heavily on debt financing. This may indicate a higher financial risk as the company has a greater obligation to repay its debt. Conversely, a lower Debt to Equity Ratio suggests a lower level of debt compared to equity, indicating a lower financial risk and a stronger equity base.

Appendix - Financial Ratio Data Preperation

In [432…

```
train_url = "/Users/hsingfentsai/Documents/Fenny/Job Search/Interview Prep/Va
df_train = pd.read_excel(train_url, sheet_name='Raw_data')
df_train = df_train[~(df_train['Financial as of'] < '2018-01-01')]
df_train.drop_duplicates(subset='UEN', inplace=True)
df_train.shape
```

Out[432…

```
(173, 36)
```

In [433…

```
df_train['Current Ratio'] = df_train['Y1_Total Current Asset'] / df_train['Y1_
df_train['Quick Ratio'] = (df_train['Y1_Total Current Asset']-df_train['Y1_In
df_train['Cash Ratio'] = df_train['Y1_Cash'] / df_train['Y1_Total Current Lia
```

In [434…

```
df_train['Solvency Ratio'] = (df_train['Y1_Net Income']+df_train['Y1_Total Am
df_train['Debt-to-Equity Ratio'] = (df_train['Y1_Term Loan']+ df_train['Y1_Lo
df_train['Debt-to-Asset Ratio'] = df_train['Y1_Total Equity'] / df_train['Y1_
```

In [435…

```
df_train.to_csv('df_train with ratio',index=False)
```

In [436…

```
df_train.shape
```

Out[436…

```
(173, 42)
```

In [442…
```
df_train_ratio = df_train.iloc[:,[0,1,2,3,36,37,38,39,40,41]]
df_train_ratio
```

Out[442…

	Application Date	UEN	Label	Financial as of	Current Ratio	Quick Ratio	Cash Ratio	Solvency Ratio
0	2018-11-13	200375496X	0	2018-11-11	1.484411	1.484411	0.097776	1.899073
1	2018-11-27	201858669V	0	2018-10-28	12.496578	12.496578	0.681838	1.370754
2	2018-11-22	201473872D	0	2018-10-28	NaN	NaN	NaN	0.354028
3	2018-11-24	201312946M	1	2018-10-21	7.342273	NaN	0.282484	1.689247
4	2018-10-18	200918909H	0	2018-10-16	1.737740	1.037651	0.007208	0.149867
...	...	...	...	...	...	...	...	...
169	2018-01-02	201113499E	0	2018-01-02	10.020273	10.020273	1.951571	0.158574
170	2018-07-24	200465108E	0	2018-01-01	3.783833	3.783833	0.000000	0.727592
171	2018-02-23	201013060G	0	2018-01-01	2.138873	2.138873	0.250193	0.291329
172	2018-01-29	201021559K	0	2018-01-01	0.228046	0.228046	0.020238	0.008458
173	2018-01-03	200618142R	0	2018-01-01	4.519627	NaN	0.313224	0.031778

173 rows × 10 columns

In [443…
```
df_train_ratio.describe()
```

Out[443…

	Label	Current Ratio	Quick Ratio	Cash Ratio	Solvency Ratio	Debt-to-Equity Ratio	Deb Asset
count	173.000000	159.000000	132.000000	160.000000	162.000000	134.000000	161.00
mean	0.127168	inf	inf	inf	inf	0.316473	0.29
std	0.334128	NaN	NaN	NaN	NaN	1.091297	0.91
min	0.000000	0.100909	0.092046	-0.001708	-3.855711	0.000000	-6.81
25%	0.000000	1.087174	0.843415	0.019201	0.105910	0.000000	0.18
50%	0.000000	1.585281	1.405428	0.108891	0.442935	0.124630	0.39
75%	0.000000	3.756447	2.534162	0.333051	1.667954	0.339986	0.56
max	1.000000	inf	inf	inf	inf	10.393590	1.00

In [451…
```
df_train.loc[df_train_ratio['UEN'] == '200976333H', 'Y1_Total Liabilities']
```

Out[451…
```
48    3300.0
Name: Y1_Total Liabilities, dtype: float64
```

In [445…
```
df_train_ratio[df_train_ratio['UEN'] == '200976333H']
```

Out[445…

	Application Date	UEN	Label	Financial as of	Current Ratio	Quick Ratio	Cash Ratio	Solven Ra
48	2018-08-09	200976333H	0	2018-05-09	35.345758	35.345758	28.400303	188.4202

In [ ]:
```
df_train[df_train['Y1_Total Current Asset'] == 0]
```

6.2. Business Implementation with Model

In addition, we can also utilize the created model to achieve the following business suggestions:

6.2.1 Credit Scoring and Risk Assessment Services:

- **Credit Risk Assessment:**

Utilize the model to evaluate the credit risk of loan applicants. Offer a credit risk assessment service that assesses the possibility of loan repayment using the model's predictions. This can give lenders a thorough evaluation of the applicant's creditworthiness so they can decide on loan approval and interest rates with additional information.

- **Loan Approval Decision Support:**

Based on the model's predictions, create a loan approval decision support system. To aid loan officers in deciding whether to approve a loan, provide a user-friendly platform that includes the model's algorithms and data analytic capabilities. Based on the applicant's financial data, the system can offer recommendations or risk scores, facilitating quicker and more precise loan approval procedures.

- **Market Insights and Loan Approval Adaptation:**

Offer lending firms regular reports and analyses that provide valuable insights into industry trends, risk factors, and comparisons to similar institutions. This service ensures up-to-date knowledge of the market landscape, enabling lenders to adjust their loan approval strategies with a deeper understanding of prevailing conditions."