Import library

```
import pandas as pd
import numpy as np
from sklearn.datasets import make_classification
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
#from sklearn.svm import SVM
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve
```

Memanggil dataset

```
ds = pd.read_csv("D:/STATISTIKA/klasifikasi__UKT_komplit.csv")
ds.head(10)
```

	No.	StatusOrtu	Penghasilan	Status_Rumah	JMotor	Jmobil	DayaLis	KIPK
0	1	1	4000000	1	1	0	2	0
1	2	1	2500000	0	1	0	3	0
2	3	1	6000000	1	2	0	2	0
3	4	1	5440500	1	2	0	2	0
4	5	1	10000000	0	1	1	3	0
5	6	1	1000000	0	1	0	3	1
6	7	1	20000000	1	2	1	3	0
7	8	1	15000000	1	1	0	3	0
8	9	4	4000000	1	1	1	3	0
9	10	1	0	1	2	0	1	0

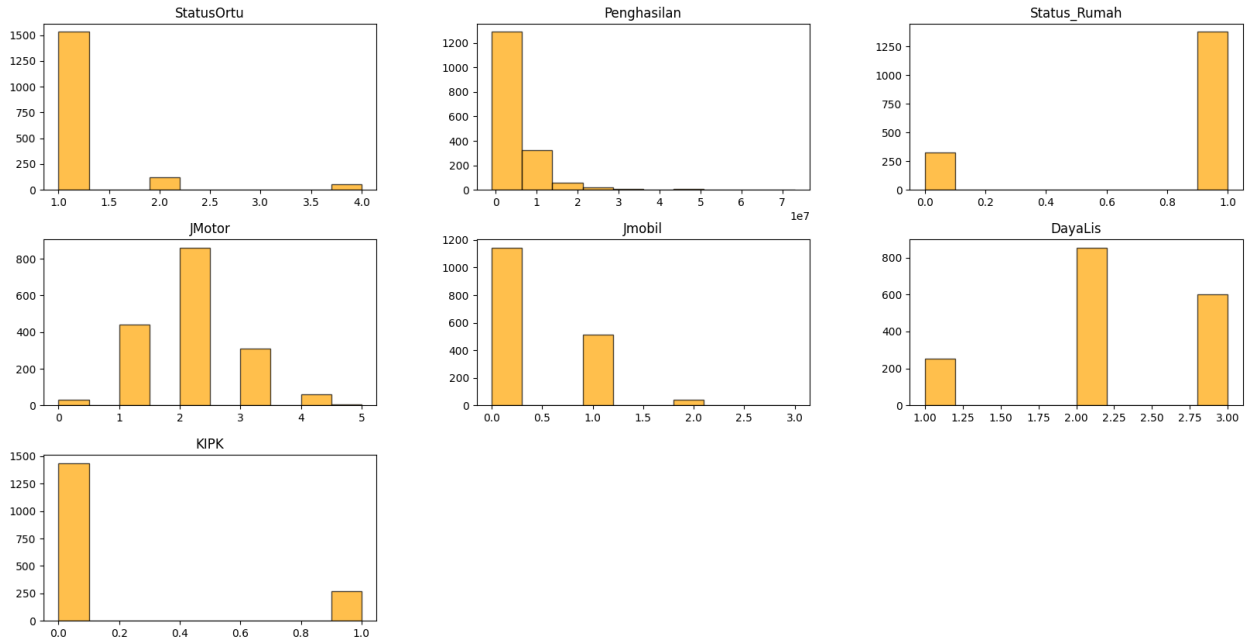
```
ds.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1707 entries, 0 to 1706
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   No.           1707 non-null   int64
 1   StatusOrtu    1707 non-null   int64
 2   Penghasilan   1707 non-null   int64
 3   Status_Rumah  1707 non-null   int64
 4   JMotor        1707 non-null   int64
 5   Jmobil        1707 non-null   int64
 6   DayaLis       1707 non-null   int64
 7   KIPK          1707 non-null   int64
dtypes: int64(8)
memory usage: 106.8 KB

ds.describe()

                No.   StatusOrtu   Penghasilan  Status_Rumah
JMotor  \
count  1707.000000  1707.000000  1.707000e+03   1707.000000
1707.000000
mean    854.000000     1.164030  5.195012e+06      0.807264
1.968366
std     492.912771     0.565764  5.552922e+06      0.394563
0.823274
min       1.000000     1.000000 -1.000000e+06      0.000000
0.000000
25%     427.500000     1.000000  2.000000e+06      1.000000
1.000000
50%     854.000000     1.000000  4.000000e+06      1.000000
2.000000
75%    1280.500000     1.000000  6.131916e+06      1.000000
2.000000
max    1707.000000     4.000000  7.300000e+07      1.000000
5.000000

            Jmobil      DayaLis         KIPK
count  1707.000000  1707.000000  1707.000000
mean      0.357938     2.205038     0.157586
std       0.541534     0.676276     0.364460
min       0.000000     1.000000     0.000000
25%       0.000000     2.000000     0.000000
50%       0.000000     2.000000     0.000000
75%       1.000000     3.000000     0.000000
max       3.000000     3.000000     1.000000
```

```
del(ds["No."])
ds.describe()
```

```
        StatusOrtu   Penghasilan  Status_Rumah       JMotor
Jmobil  \
count  1707.000000  1.707000e+03   1707.000000  1707.000000
1707.000000
mean      1.164030  5.195012e+06      0.807264     1.968366
0.357938
std       0.565764  5.552922e+06      0.394563     0.823274
0.541534
min       1.000000 -1.000000e+06      0.000000     0.000000
0.000000
25%       1.000000  2.000000e+06      1.000000     1.000000
0.000000
50%       1.000000  4.000000e+06      1.000000     2.000000
0.000000
75%       1.000000  6.131916e+06      1.000000     2.000000
1.000000
max       4.000000  7.300000e+07      1.000000     5.000000
3.000000

           DayaLis         KIPK
count  1707.000000  1707.000000
mean      2.205038     0.157586
std       0.676276     0.364460
min       1.000000     0.000000
25%       2.000000     0.000000
50%       2.000000     0.000000
75%       3.000000     0.000000
max       3.000000     1.000000
```

```
histogram = ds
histogram.hist(figsize=(20,10),alpha = 0.7, color =
'orange',edgecolor ='black',grid=False)
```

```
array([[<Axes: title={'center': 'StatusOrtu'}>,
        <Axes: title={'center': 'Penghasilan'}>,
        <Axes: title={'center': 'Status_Rumah'}>],
       [<Axes: title={'center': 'JMotor'}>,
        <Axes: title={'center': 'Jmobil'}>,
        <Axes: title={'center': 'DayaLis'}>],
       [<Axes: title={'center': 'KIPK'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



Output di atas adalah hasil plot untuk distribusi tiap fitur dataset, Disini didapat 4 fitur merupakan categorical variable dan sisanya berupa numerical variable

```
from sklearn.preprocessing import MinMaxScaler
array = ds.values
x = array[:,1:6] #slicing dataframe kedalam array
y = array[:,6]

scaler = MinMaxScaler()
#transformasi data
x = scaler.fit_transform(x)
x
```

```
array([[0.06756757, 1.        , 0.2       , 0.        , 0.5       ],
       [0.0472973 , 0.        , 0.2       , 0.        , 1.        ],
       [0.09459459, 1.        , 0.4       , 0.        , 0.5       ],
       ...,
       [0.02567568, 1.        , 0.6       , 0.33333333, 0.5       ],
       [0.08108108, 0.        , 0.4       , 0.        , 0.        ],
       [0.12162162, 1.        , 0.6       , 0.        , 0.5       ]])
```

Disini saya terapkan normalisasi data yaitu minmaxscaler

```
y = y.astype('int')
y
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

```
Counter(y)
```

```
Counter({0: 1438, 1: 269})
```

Hasil dari target berupa logit biner dengan memanggil Counter(y), maka didapat jumlah tiap target

```
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2,
random_state=2)
# instantiating the random over sampler
ros = RandomOverSampler()
# resampling x_train, y_train
X_ros, y_ros = ros.fit_resample(x_train, y_train)
# new class distribution
print(Counter(y_ros))

Counter({0: 1156, 1: 1156})
```

untuk mengatasi dataset yang tidak seimbang. Disini digunakan function RandomOverSample untuk. towardds the majority class, untuk memprediksi random, Data yang telah di pisah data train dan data test kemudian

```
logmodel = LogisticRegression()

#1 model dengan dataset asli
model1=logmodel.fit(x_train, y_train)
predictions1a = model1.predict(x_train)
predictions1b = model1.predict(x_test)
predictions1c = model1.predict_proba(x_test)[:,1]
print("-------Model-1: Logit Biner dengan Dataset Asli-------")
print("Kinerja Data Training:")
print(classification_report(y_train, predictions1a))
print(confusion_matrix(y_train, predictions1a))
print(accuracy_score(y_train, predictions1a))
print("Kinerja Data Testing:")
print(classification_report(y_test, predictions1b))
print(confusion_matrix(y_test, predictions1b))
print(accuracy_score(y_test, predictions1b))

-------Model-1: Logit Biner dengan Dataset Asli-------
Kinerja Data Training:
              precision    recall  f1-score   support

           0       0.85      0.99      0.92      1156
           1       0.48      0.06      0.11       209

    accuracy                           0.85      1365
   macro avg       0.67      0.53      0.51      1365
```

```
weighted avg       0.80      0.85      0.79      1365

[[1142   14]
 [ 196   13]]
0.8461538461538461
Kinerja Data Testing:
              precision    recall  f1-score   support

           0       0.83      0.98      0.90       282
           1       0.33      0.05      0.09        60

    accuracy                           0.82       342
   macro avg       0.58      0.51      0.49       342
weighted avg       0.74      0.82      0.76       342

[[276   6]
 [ 57   3]]
0.8157894736842105
```

Klasifikasi report dan confusion matrix dari data train dan data test menghasilkan kinerja dari data testing dan data train yang tidak beda jauh, yang menunjukkan bahwa model bekerja dengan sangat baik

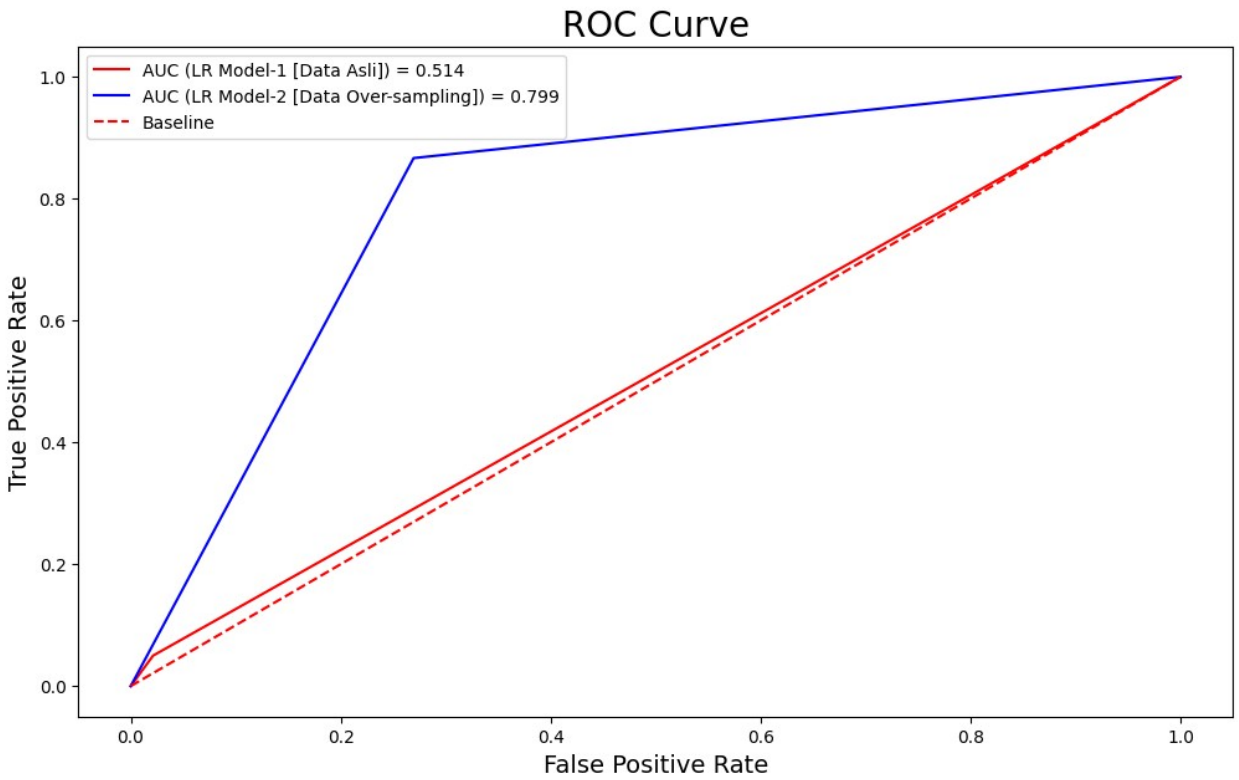
```
model2=logmodel.fit(X_ros, y_ros)
predictions2a = model2.predict(X_ros)
predictions2b = model2.predict(x_test)
predictions2c = model2.predict_proba(x_test)[:,1]
print("-------Model-2: Logit Biner dengan Dataset Over-
sampling-------")
print("Kinerja Data Training:")
print(classification_report(y_ros, predictions2a))
print(confusion_matrix(y_ros, predictions2a))
print(accuracy_score(y_ros, predictions2a))
print("Kinerja Data Testing:")
print(classification_report(y_test, predictions2b))
print(confusion_matrix(y_test, predictions2b))
print(accuracy_score(y_test, predictions2b))
```

```
-------Model-2: Logit Biner dengan Dataset Over-sampling-------
Kinerja Data Training:
              precision    recall  f1-score   support

           0       0.82      0.68      0.74      1156
           1       0.73      0.85      0.78      1156

    accuracy                           0.76      2312
   macro avg       0.77      0.76      0.76      2312
weighted avg       0.77      0.76      0.76      2312
```

```
[[787 369]
 [178 978]]
0.7634083044982699
Kinerja Data Testing:
              precision    recall  f1-score   support

           0       0.96      0.73      0.83       282
           1       0.41      0.87      0.55        60

    accuracy                           0.75       342
   macro avg       0.68      0.80      0.69       342
weighted avg       0.87      0.75      0.78       342

[[206  76]
 [  8  52]]
0.7543859649122807
```

Klasifikasi report dan confusion matrix dari data train dan data test yang telah diresampling, menghasilkan kinerja dari data testing dan data train yang tidak beda jauh, yang menunjukkan bahwa model bekerja dengan sangat baik. meski besgitu nilai yang dihasilkan sedikit lebih kecil dari data tanpa diresampling.

```
#y_test_int = y_test.replace({'Good': 1, 'Bad': 0})
auc1 = roc_auc_score(y_test, predictions1b)
fpr1, tpr1, thresholds1 = roc_curve(y_test, predictions1b)
auc2 = roc_auc_score(y_test, predictions2b)
fpr2, tpr2, thresholds2 = roc_curve(y_test, predictions2b)
plt.figure(figsize=(12, 7))
plt.plot(fpr1, tpr1, label=f'AUC (LR Model-1 [Data Asli]) =
{auc1:.3f}',color='red')
plt.plot(fpr2, tpr2, label=f'AUC (LR Model-2 [Data Over-sampling]) =
{auc2:.3f}',color='blue')
plt.plot([0, 1], [0, 1], color='red', linestyle='--',
label='Baseline')
plt.title('ROC Curve', size=20)
plt.xlabel('False Positive Rate', size=14)
plt.ylabel('True Positive Rate', size=14)
plt.legend()

<matplotlib.legend.Legend at 0x1ac5ed80450>
```



Hasil output menampilkan perbandingan hasil data train dan test dengan data resampling dan data asli.

Import library

```
import pandas as pd
import statsmodels.formula.api as smf
import numpy as np
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

ds = pd.read_csv("D:/STATISTIKA\BANK LOAN.csv")
ds
```

```
     age  ed  employ  address  income  debtinc   creddebt   othdebt
default
0     41   3      17       12     176      9.3  11.359392  5.008608
1
1     27   1      10        6      31     17.3   1.362202  4.000798
0
2     40   1      15       14      55      5.5   0.856075  2.168925
0
3     41   1      15       14     120      2.9   2.658720  0.821280
0
4     24   2       2        0      28     17.3   1.787436  3.056564
1
..   ...  ..     ...      ...     ...      ...        ...       ...
...
695   36   2       6       15      27      4.6   0.262062  0.979938
1
696   29   2       6        4      21     11.5   0.369495  2.045505
0
697   33   1      15        3      32      7.6   0.491264  1.940736
0
698   45   1      19       22      77      8.4   2.302608  4.165392
0
699   37   1      12       14      44     14.7   2.994684  3.473316
0

[700 rows x 9 columns]
```

Menampilkan eksplanatory data analitik dari data BANK LOAN

```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700 entries, 0 to 699
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
```

```
 0   age       700 non-null    int64
 1   ed        700 non-null    int64
 2   employ    700 non-null    int64
 3   address   700 non-null    int64
 4   income    700 non-null    int64
 5   debtinc   700 non-null    float64
 6   creddebt  700 non-null    float64
 7   othdebt   700 non-null    float64
 8   default   700 non-null    int64
dtypes: float64(3), int64(6)
memory usage: 49.3 KB
```

```
ds['age'] = pd.cut(ds['age'], bins=[0,28,40,150],
labels=['1','2','3'])
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700 entries, 0 to 699
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       700 non-null    category
 1   ed        700 non-null    int64
 2   employ    700 non-null    int64
 3   address   700 non-null    int64
 4   income    700 non-null    int64
 5   debtinc   700 non-null    float64
 6   creddebt  700 non-null    float64
 7   othdebt   700 non-null    float64
 8   default   700 non-null    int64
dtypes: category(1), float64(3), int64(5)
memory usage: 44.7 KB
```

```
ds.head(10)
```

```
  age  ed  employ  address  income  debtinc   creddebt    othdebt
default
0   3   3      17       12     176      9.3  11.359392   5.008608
1
1   1   1      10        6      31     17.3   1.362202   4.000798
0
2   2   1      15       14      55      5.5   0.856075   2.168925
0
3   3   1      15       14     120      2.9   2.658720   0.821280
0
4   1   2       2        0      28     17.3   1.787436   3.056564
1
5   3   2       5        5      25     10.2   0.392700   2.157300
0
6   2   1      20        9      67     30.6   3.833874  16.668126
```

```
0
7   3   1      12       11      38      3.6   0.128592   1.239408
0
8   1   1       3        4      19     24.4   1.358348   3.277652
1
9   2   1       0       13      25     19.7   2.777700   2.147300
0

resiko_model = smf.logit(formula='default ~ age + employ + address +
debtinc + creddebt + othdebt',
                         data = ds).fit()
resiko_model.summary()

Optimization terminated successfully.
         Current function value: 0.395614
         Iterations 7

<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

==============================================================================
========
Dep. Variable:                 default   No. Observations:
700
Model:                           Logit   Df Residuals:
692
Method:                            MLE   Df Model:
7
Date:                Thu, 28 Mar 2024   Pseudo R-squ.:
0.3114
Time:                        09:42:06   Log-Likelihood:
-276.93
converged:                       True   LL-Null:
-402.18
Covariance Type:            nonrobust   LLR p-value:
2.164e-50
==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept     -0.7984      0.271     -2.950      0.003      -1.329
-0.268
age[T.2]       0.1782      0.269      0.662      0.508      -0.349
0.706
age[T.3]       0.5988      0.381      1.571      0.116      -0.148
1.346
employ        -0.2596      0.032     -8.105      0.000      -0.322
```

```
-0.197
address        -0.0978      0.023     -4.336      0.000       -0.142
-0.054
debtinc         0.0849      0.022      3.842      0.000        0.042
0.128
creddebt        0.5641      0.089      6.310      0.000        0.389
0.739
othdebt         0.0231      0.057      0.405      0.686       -0.089
0.135
==============================================================================
========
"""

resiko_model = smf.logit(formula='default ~ employ + address + debtinc
+ creddebt',
                         data = ds).fit()
resiko_model.summary()

Optimization terminated successfully.
         Current function value: 0.397665
         Iterations 7

<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

==============================================================================
========
Dep. Variable:                default   No. Observations:
700
Model:                          Logit   Df Residuals:
695
Method:                           MLE   Df Model:
4
Date:                Thu, 28 Mar 2024   Pseudo R-squ.:
0.3079
Time:                        09:42:06   Log-Likelihood:
-278.37
converged:                       True   LL-Null:
-402.18
Covariance Type:            nonrobust   LLR p-value:
2.106e-52
==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept     -0.7911      0.252     -3.145      0.002      -1.284
-0.298
```

```
employ         -0.2426      0.028     -8.646      0.000      -0.298
-0.188
address        -0.0812      0.020     -4.145      0.000      -0.120
-0.043
debtinc         0.0883      0.019      4.760      0.000       0.052
0.125
creddebt        0.5730      0.087      6.566      0.000       0.402
0.744
==============================================================================
========
"""
```

Kedua hasil OLS di atas adalah tampilan summary dari logistic regresion menggunakan OLS. Dimana di logit model kedua dengan tanpa atribut umur menghasilkan nilai yang sedikit lebih tinggi.

```
conf = resiko_model.conf_int()
conf['OR'] = resiko_model.params
conf.columns = ['2.5%', '97.5%', 'OR']
print(np.exp(conf))
```

```
                2.5%     97.5%        OR
Intercept   0.276905  0.742263  0.453361
employ      0.742606  0.828941  0.784587
address     0.887222  0.958073  0.921967
debtinc     1.053295  1.132707  1.092279
creddebt    1.494738  2.104432  1.773577
```

Hasil output merupakan nilai interval kepercayaan (confidence interval) dan nilai Odds Ratio (OR) dari model logit. Besaran nilai merupakan ukuran dari seberapa besar kemungkinan perubahan pada variabel independen mempengaruhi peluang kejadian pada variabel dependen.

```
predicted_value1 = resiko_model.predict()
threshold =  0.5 #persentase
predicted_class1 = np.zeros(predicted_value1.shape)
predicted_class1[predicted_value1>threshold]=1
cm1 = confusion_matrix(ds['default'], predicted_class1)
print('confusion matrix  : \n', cm1)
```

```
confusion matrix  :
 [[478  39]
 [ 91  92]]
```

Menampilkan hasil confusion matrix dari model logit, hal ini dilakukan untuk mengidentifikasi metrik evaluasi

```
sensitivity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Sensitivity : ', sensitivity)
specifity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Specifity : ', specifity)

Sensitivity :  0.5027322404371585
Specifity :  0.9245647969052224
```

Model memiliki tingkat sensitivitas sekitar 50.27%, yang mengindikasikan bahwa hanya sekitar separuh dari kasus positif aktual yang diprediksi dengan benar oleh model. Di sisi lain, tingkat spesifisitas model sekitar 92.46%, yang menunjukkan bahwa sebagian besar kasus negatif aktual diprediksi dengan benar oleh model.

```
print(classification_report(ds['default'], predicted_class1))

              precision    recall  f1-score   support

           0       0.84      0.92      0.88       517
           1       0.70      0.50      0.59       183

    accuracy                           0.81       700
   macro avg       0.77      0.71      0.73       700
weighted avg       0.80      0.81      0.80       700
```

Terakhir menampilkan hasil confusion matrix dari model logit