DataMining_LoanApproval

January 18, 2025

Loan Approval Prediction using Machine Learning

[1]:
```
#importing relevant packages

import numpy as np
import pandas as pd

#import packages for data visualization

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV

from sklearn.metrics import classification_report, confusion_matrix,␣
↪ConfusionMatrixDisplay
import sklearn.metrics as metrics

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier, plot_importance

import pickle
```

[2]:
```
#loading the dataset into a dataframe
data = pd.read_csv("Loan_approval.csv")
```

[3]:
```
#display first few rows of the dataframe
data.head()
```

[3]:
```
   id  person_age  person_income person_home_ownership  person_emp_length  \
0   0          37          35000                  RENT                0.0
1   1          22          56000                   OWN                6.0
2   2          29          28800                   OWN                8.0
3   3          30          70000                  RENT               14.0
```

```
4   4          22          60000                  RENT               2.0

  loan_intent loan_grade  loan_amnt  loan_int_rate  loan_percent_income  \
0   EDUCATION          B       6000          11.49                 0.17
1     MEDICAL          C       4000          13.35                 0.07
2    PERSONAL          A       6000           8.90                 0.21
3     VENTURE          B      12000          11.11                 0.17
4     MEDICAL          A       6000           6.92                 0.10

  cb_person_default_on_file  cb_person_cred_hist_length  loan_status
0                         N                          14            0
1                         N                           2            0
2                         N                          10            0
3                         N                           5            0
4                         N                           3            0
```

[4]:
```python
#display the number of rows and columns

data.shape
```

[4]:
```
(58645, 13)
```

[5]:
```python
# Get the basic information about the data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58645 entries, 0 to 58644
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          58645 non-null  int64
 1   person_age                  58645 non-null  int64
 2   person_income               58645 non-null  int64
 3   person_home_ownership       58645 non-null  object
 4   person_emp_length           58645 non-null  float64
 5   loan_intent                 58645 non-null  object
 6   loan_grade                  58645 non-null  object
 7   loan_amnt                   58645 non-null  int64
 8   loan_int_rate               58645 non-null  float64
 9   loan_percent_income         58645 non-null  float64
 10  cb_person_default_on_file   58645 non-null  object
 11  cb_person_cred_hist_length  58645 non-null  int64
 12  loan_status                 58645 non-null  int64
dtypes: float64(3), int64(6), object(4)
memory usage: 5.8+ MB
```

[6]:
```python
#Check the summary statistics of the numerical values in the data
data.describe()
```

[6]:

```
                 id    person_age  person_income  person_emp_length  \
count  58645.000000  58645.000000   5.864500e+04       58645.000000
mean   29322.000000     27.550857   6.404617e+04           4.701015
std    16929.497605      6.033216   3.793111e+04           3.959784
min        0.000000     20.000000   4.200000e+03           0.000000
25%    14661.000000     23.000000   4.200000e+04           2.000000
50%    29322.000000     26.000000   5.800000e+04           4.000000
75%    43983.000000     30.000000   7.560000e+04           7.000000
max    58644.000000    123.000000   1.900000e+06         123.000000

          loan_amnt  loan_int_rate  loan_percent_income  \
count  58645.000000   58645.000000         58645.000000
mean    9217.556518      10.677874             0.159238
std     5563.807384       3.034697             0.091692
min      500.000000       5.420000             0.000000
25%     5000.000000       7.880000             0.090000
50%     8000.000000      10.750000             0.140000
75%    12000.000000      12.990000             0.210000
max    35000.000000      23.220000             0.830000

       cb_person_cred_hist_length   loan_status
count                58645.000000  58645.000000
mean                     5.813556      0.142382
std                      4.029196      0.349445
min                      2.000000      0.000000
25%                      3.000000      0.000000
50%                      4.000000      0.000000
75%                      8.000000      0.000000
max                     30.000000      1.000000
```

[7]:

```python
# Check for missing values
data.isna().sum()
```

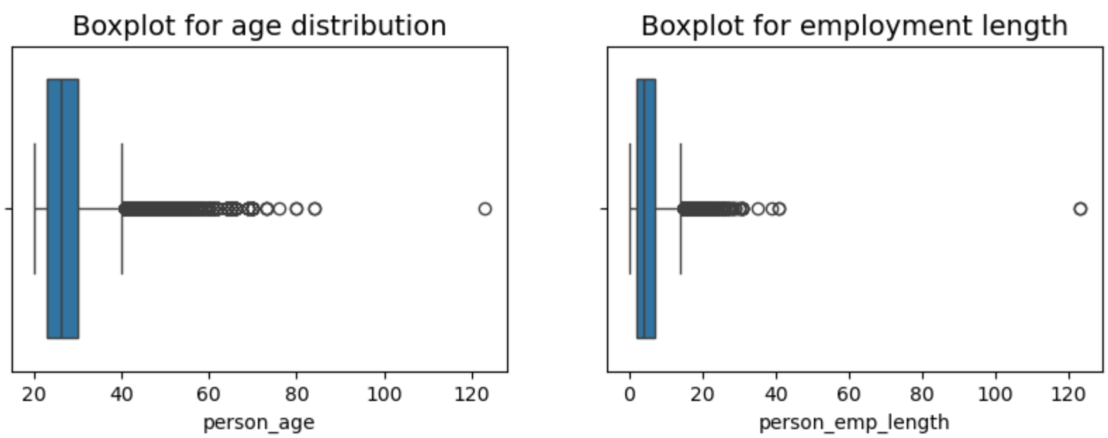
[7]:

```
id                            0
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
loan_status                   0
dtype: int64
```

[8]:
```
# Check for duplicates
data.duplicated().sum()
```

[8]: 0

[9]:
```
# plot a boxplot for age and person_emp_length to identify outliers
fig, ax= plt.subplots(1,2, figsize=(10,3))
sns.boxplot(data=data, x='person_age', orient= 'h', ax=ax[0])
ax[0].set_title('Boxplot for age distribution', fontsize='14')
sns.boxplot(data=data, x='person_emp_length', ax=ax[1])
ax[1].set_title('Boxplot for employment length', fontsize='14')

plt.show()
```



Above Box plot for age and person_emp_length has one row each with value 123 which are outliers

[10]:
```
# removing rows with person_age=123 and person_emp_length=123
df1=data[(data['person_age']!= 123) & (data['person_emp_length']!= 123)]
```

[11]:
```
df1.describe()
```

[11]:

	id	person_age	person_income	person_emp_length	\
count	58642.000000	58642.000000	5.864200e+04	58642.000000	
mean	29321.152468	27.549333	6.404453e+04	4.696941	
std	16929.497527	6.020420	3.792822e+04	3.899139	
min	0.000000	20.000000	4.200000e+03	0.000000	
25%	14660.250000	23.000000	4.200000e+04	2.000000	
50%	29320.500000	26.000000	5.800000e+04	4.000000	
75%	43981.750000	30.000000	7.560000e+04	7.000000	
max	58644.000000	84.000000	1.900000e+06	41.000000	

loan_amnt   loan_int_rate   loan_percent_income   \

```
count  58642.000000   58642.000000         58642.000000
mean    9217.146448      10.677770             0.159235
std     5563.380070       3.034695             0.091690
min      500.000000       5.420000             0.000000
25%     5000.000000       7.880000             0.090000
50%     8000.000000      10.750000             0.140000
75%    12000.000000      12.990000             0.210000
max    35000.000000      23.220000             0.830000

       cb_person_cred_hist_length   loan_status
count                58642.000000  58642.000000
mean                     5.813649      0.142372
std                      4.029261      0.349435
min                      2.000000      0.000000
25%                      3.000000      0.000000
50%                      4.000000      0.000000
75%                      8.000000      0.000000
max                     30.000000      1.000000
```

[12]:
```
#saving the cleaned file to csv for further data visualization in tableau

df1.to_csv('data_loan_cleaned.csv', index=False)
```

[13]:
```
#loading the cleaned dataset to variable data for further modeling
data= pd.read_csv('data_loan_cleaned.csv')
```

[14]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58642 entries, 0 to 58641
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          58642 non-null  int64
 1   person_age                  58642 non-null  int64
 2   person_income               58642 non-null  int64
 3   person_home_ownership       58642 non-null  object
 4   person_emp_length           58642 non-null  float64
 5   loan_intent                 58642 non-null  object
 6   loan_grade                  58642 non-null  object
 7   loan_amnt                   58642 non-null  int64
 8   loan_int_rate               58642 non-null  float64
 9   loan_percent_income         58642 non-null  float64
 10  cb_person_default_on_file   58642 non-null  object
 11  cb_person_cred_hist_length  58642 non-null  int64
 12  loan_status                 58642 non-null  int64
dtypes: float64(3), int64(6), object(4)
memory usage: 5.8+ MB
```

[15]:
```
# Check the class balance for the target variable 'loan_status'
data['loan_status'].value_counts(normalize= True)
```

[15]:
```
loan_status
0    0.857628
1    0.142372
Name: proportion, dtype: float64
```

The class balance here is 85% to 15% which isnt ideal but not worse. And since dataset has enough number of both positive and negative classes, we continue without any further balancing like over sampling or down-sampling as it might result overfitting

[16]:
```
#understanding the catogorical variables and converting them into numerical␣
↪values
data['person_home_ownership'].value_counts()
```

[16]:
```
person_home_ownership
RENT        30594
MORTGAGE    24821
OWN          3138
OTHER          89
Name: count, dtype: int64
```

[17]:
```
data['loan_grade'].value_counts()
```

[17]:
```
loan_grade
A    20984
B    20398
C    11036
D     5033
E     1009
F      149
G       33
Name: count, dtype: int64
```

[18]:
```
data['loan_intent'].value_counts()
```

[18]:
```
loan_intent
EDUCATION            12271
MEDICAL              10933
PERSONAL             10015
VENTURE              10010
DEBTCONSOLIDATION     9133
HOMEIMPROVEMENT       6280
Name: count, dtype: int64
```

[19]:
```
data['cb_person_default_on_file'].value_counts()
```

[19]:
```
cb_person_default_on_file
N    49941
Y     8701
Name: count, dtype: int64
```

[20]:
```
#converting all the catogorical variables into dummy encode for the modeling␣
↪and save to new variable
df_encoded= pd.get_dummies(data, drop_first = 'True', dtype = int)
df_encoded.head()
```

[20]:
```
   id  person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
0   0          37          35000                0.0       6000          11.49
1   1          22          56000                6.0       4000          13.35
2   2          29          28800                8.0       6000           8.90
3   3          30          70000               14.0      12000          11.11
4   4          22          60000                2.0       6000           6.92

   loan_percent_income  cb_person_cred_hist_length  loan_status  \
0                 0.17                          14            0
1                 0.07                           2            0
2                 0.21                          10            0
3                 0.17                           5            0
4                 0.10                           3            0

   person_home_ownership_OTHER  …  loan_intent_MEDICAL  \
0                            0  …                    0
1                            0  …                    1
2                            0  …                    0
3                            0  …                    0
4                            0  …                    1

   loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
0                     0                    0             1             0
1                     0                    0             0             1
2                     1                    0             0             0
3                     0                    1             1             0
4                     0                    0             0             0

   loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
0             0             0             0             0
1             0             0             0             0
2             0             0             0             0
3             0             0             0             0
4             0             0             0             0

   cb_person_default_on_file_Y
0                            0
```

```
1                             0
2                             0
3                             0
4                             0

[5 rows x 24 columns]
```

[21]:
```python
# removing column 'id' as its no longer user for modeling
df_encoded = df_encoded.drop('id', axis=1)
```

[22]:
```python
# defining the target variable
y= df_encoded['loan_status']

# defining the predictor variables by removing the 'loan_status' and 'id'
X = df_encoded.drop('loan_status', axis = 1)

# printing first few rows of both X and y variables
print(X.head())
print(y.head())
```

```
   person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
0          37          35000                0.0       6000          11.49
1          22          56000                6.0       4000          13.35
2          29          28800                8.0       6000           8.90
3          30          70000               14.0      12000          11.11
4          22          60000                2.0       6000           6.92

   loan_percent_income  cb_person_cred_hist_length  \
0                 0.17                          14
1                 0.07                           2
2                 0.21                          10
3                 0.17                           5
4                 0.10                           3

   person_home_ownership_OTHER  person_home_ownership_OWN  \
0                            0                          0
1                            0                          1
2                            0                          1
3                            0                          0
4                            0                          0

   person_home_ownership_RENT  …  loan_intent_MEDICAL  loan_intent_PERSONAL  \
0                           1  …                    0                     0
1                           0  …                    1                     0
2                           0  …                    0                     1
3                           1  …                    0                     0
4                           1  …                    1                     0
```

```
   loan_intent_VENTURE  loan_grade_B  loan_grade_C  loan_grade_D  \
0                    0             1             0             0
1                    0             0             1             0
2                    0             0             0             0
3                    1             1             0             0
4                    0             0             0             0

   loan_grade_E  loan_grade_F  loan_grade_G  cb_person_default_on_file_Y
0             0             0             0                            0
1             0             0             0                            0
2             0             0             0                            0
3             0             0             0                            0
4             0             0             0                            0

[5 rows x 22 columns]
0    0
1    0
2    0
3    0
4    0
Name: loan_status, dtype: int64
```

[23]:
```python
# splitting data into train and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.3,␣
↪stratify = y, random_state = 42)
    X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[23]:
```
((41049, 22), (17593, 22), (41049,), (17593,))
```

[24]:
```python
# instantiate logistics regression model
clf= LogisticRegression()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.93     15088
           1       0.70      0.31      0.43      2505

    accuracy                           0.88     17593
   macro avg       0.80      0.64      0.68     17593
weighted avg       0.87      0.88      0.86     17593


C:\Users\nibin\anaconda3\Lib\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[25]:

```python
print("Accuracy:", "%.6f" % metrics.accuracy_score(y_test, y_pred))
print("Precision:", "%.6f" % metrics.precision_score(y_test, y_pred))
print("Recall:", "%.6f" % metrics.recall_score(y_test, y_pred))
print("F1 Score:", "%.6f" % metrics.f1_score(y_test, y_pred))
```

```
Accuracy: 0.882737
Precision: 0.699099
Recall: 0.309780
F1 Score: 0.429322
```

The scores arent promising. This could be because the data isnt scaled. When the dataset is scaled and run again for the logistic regression, the results may get better.

[26]:

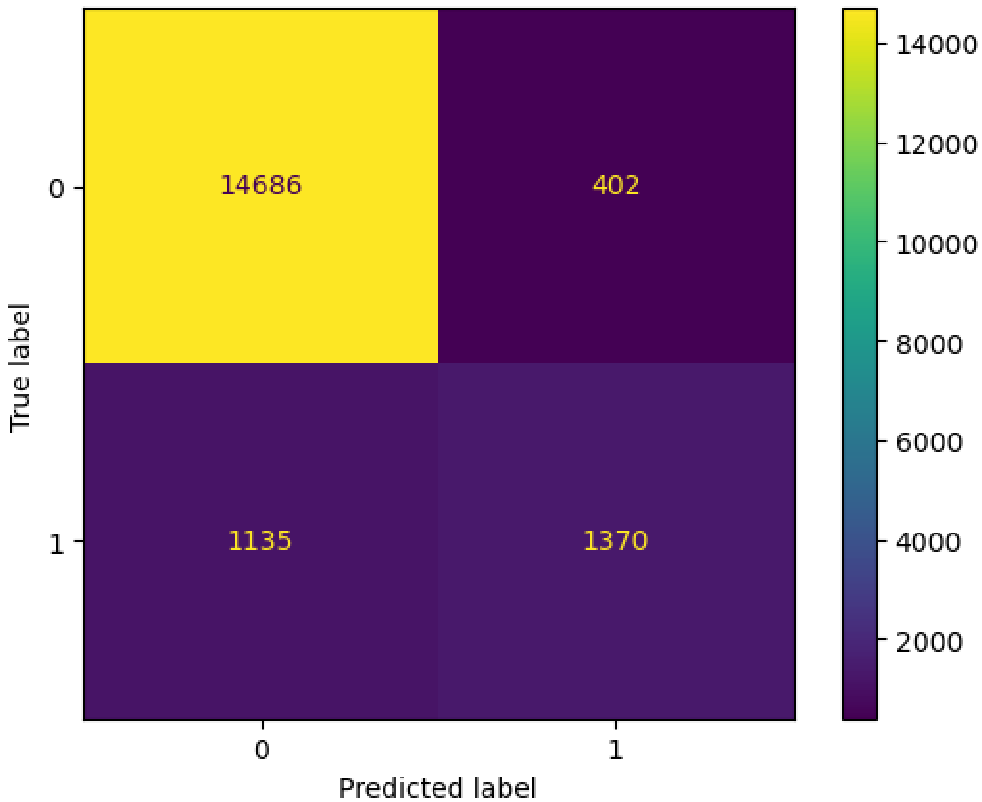
```python
# creating a pipeline to scale the data and to run logistic regression

steps = [('scaler', StandardScaler()), ('log_reg', LogisticRegression())]
pipeline = Pipeline(steps)
log_reg_scaled = pipeline.fit(X_train, y_train)
y_pred_scaled = log_reg_scaled.predict(X_test)
print(classification_report(y_test, y_pred_scaled))
```

```
              precision    recall  f1-score   support

           0       0.93      0.97      0.95     15088
           1       0.77      0.55      0.64      2505

    accuracy                           0.91     17593
   macro avg       0.85      0.76      0.80     17593
weighted avg       0.91      0.91      0.91     17593
```

[27]:

```python
cm= confusion_matrix(y_test, y_pred_scaled, labels = log_reg_scaled.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels=␣
 ↪log_reg_scaled.classes_)
disp.plot()
```

[27]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1de41e09160>



[28]:
```
print("Accuracy:", "%.6f" % metrics.accuracy_score(y_test, y_pred_scaled))
print("Precision:", "%.6f" % metrics.precision_score(y_test, y_pred_scaled))
print("Recall:", "%.6f" % metrics.recall_score(y_test, y_pred_scaled))
print("F1 Score:", "%.6f" % metrics.f1_score(y_test, y_pred_scaled))
```

```
Accuracy: 0.912636
Precision: 0.773138
Recall: 0.546906
F1 Score: 0.640636
```

[29]:
```
# Random Forest Model and XGBoost

rf = RandomForestClassifier(random_state = 0)
# Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [5, None],
             'max_features': [0.3, 0.6],
             'max_samples': [0.7],
             'n_estimators': [75,100,125,150],
             }

# Define a dictionary of scoring metrics to capture
```

```
scoring = {'accuracy':'accuracy', 'precision':'precision', 'recall':'recall',␣
↪'f1':'f1'}

# Instantiate the GridSearchCV object
rf_cv = GridSearchCV(rf, cv_params,scoring = scoring, refit = 'precision', cv=5)
```

[30]:
```
# %time
#rf_cv.fit(X_train, y_train)
```

[31]:
```
# Pickle the model
#with open('rf_cv_model.pickle', 'wb') as file:
#    pickle.dump(rf_cv, file)
```

[32]:
```
# Read in pickled model
with open('rf_cv_model.pickle', 'rb') as file:
 rf_cv = pickle.load(file)
```

[33]:
```
rf_cv.best_score_
```

[33]: 0.9501815170034851

[35]:
```
y_pred_rf = rf_cv.best_estimator_.predict(X_test)
```

[36]:
```
 print("Accuracy:", "%.6f" % metrics.accuracy_score(y_test, y_pred_rf))
 print("Precision:", "%.6f" % metrics.precision_score(y_test, y_pred_rf))
 print("Recall:", "%.6f" % metrics.recall_score(y_test, y_pred_rf))
 print("F1 Score:", "%.6f" % metrics.f1_score(y_test, y_pred_rf))
```

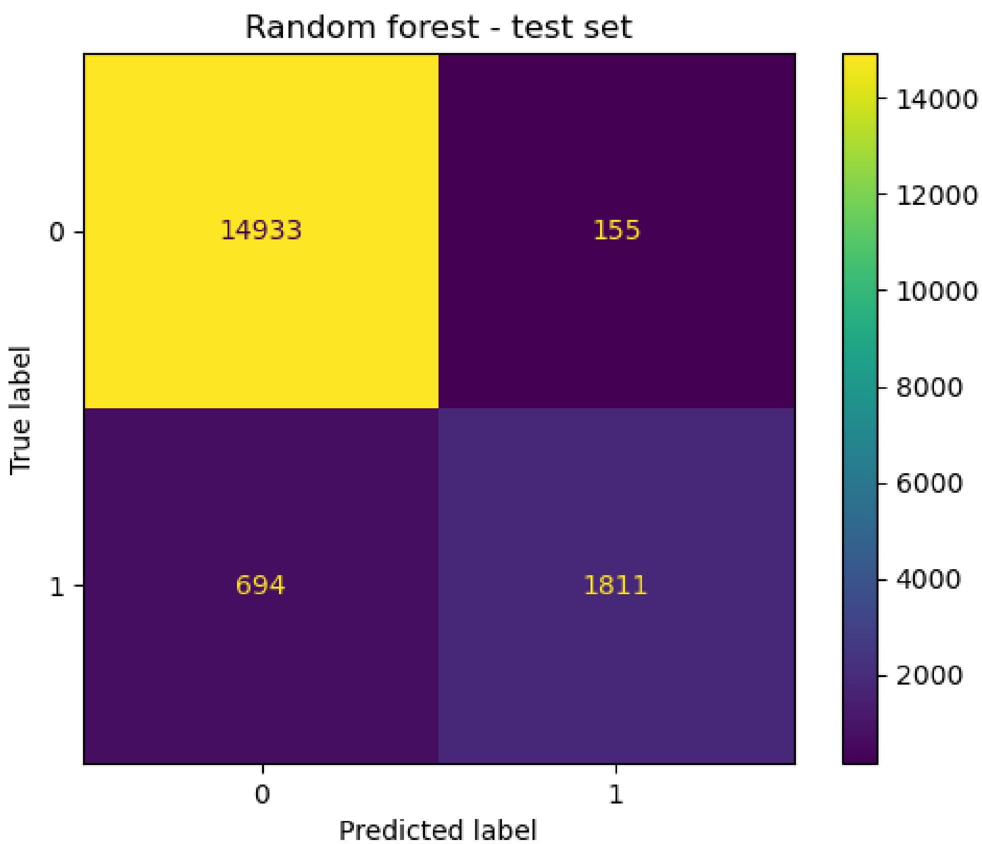
```
Accuracy: 0.951742
Precision: 0.921160
Recall: 0.722954
F1 Score: 0.810110
```

[37]:
```
print(classification_report(y_test, y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.97     15088
           1       0.92      0.72      0.81      2505

    accuracy                           0.95     17593
   macro avg       0.94      0.86      0.89     17593
weighted avg       0.95      0.95      0.95     17593
```

[38]:
```
# Compute values for confusion matrix
rf_cm = confusion_matrix(y_test, y_pred_rf)
```

```
# Create display of confusion matrix
rf_disp = ConfusionMatrixDisplay(confusion_matrix=rf_cm, display_labels=None)

# Plot confusion matrix
rf_disp.plot()

# Display plot
plt.title('Random forest - test set');
plt.show()
```



[39]:
```
# Instantiate the XGBoost classifier
xgb = XGBClassifier(objective='binary:logistic', random_state=0)

# Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [7,8,9,None],
             'min_child_weight': [3, 5],
             'learning_rate': [0.01, 0.1],
             'n_estimators': [100,150,175]
             }
```

```
# Define a dictionary of scoring metrics to capture
scoring = {'accuracy':'accuracy', 'precision':'precision', 'recall':'recall',␣
↪'f1':'f1'}

# Instantiate the GridSearchCV object
xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=6, refit='f1')
```

[40]:
```
#%time
#xgb_cv.fit(X_train, y_train)
```

[41]:
```
#Pickle the model
#with open('xgb_cv_model.pickle', 'wb') as file:
#    pickle.dump(xgb_cv, file)
```

[42]:
```
# Read in pickled model
with open('xgb_cv_model.pickle', 'rb') as file:
 xgb_cv = pickle.load(file)
```

[43]:
```
print(xgb_cv.best_score_)
print(xgb_cv.best_params_)
```

```
0.8112010608905319
{'learning_rate': 0.1, 'max_depth': 7, 'min_child_weight': 5, 'n_estimators':
175}
```

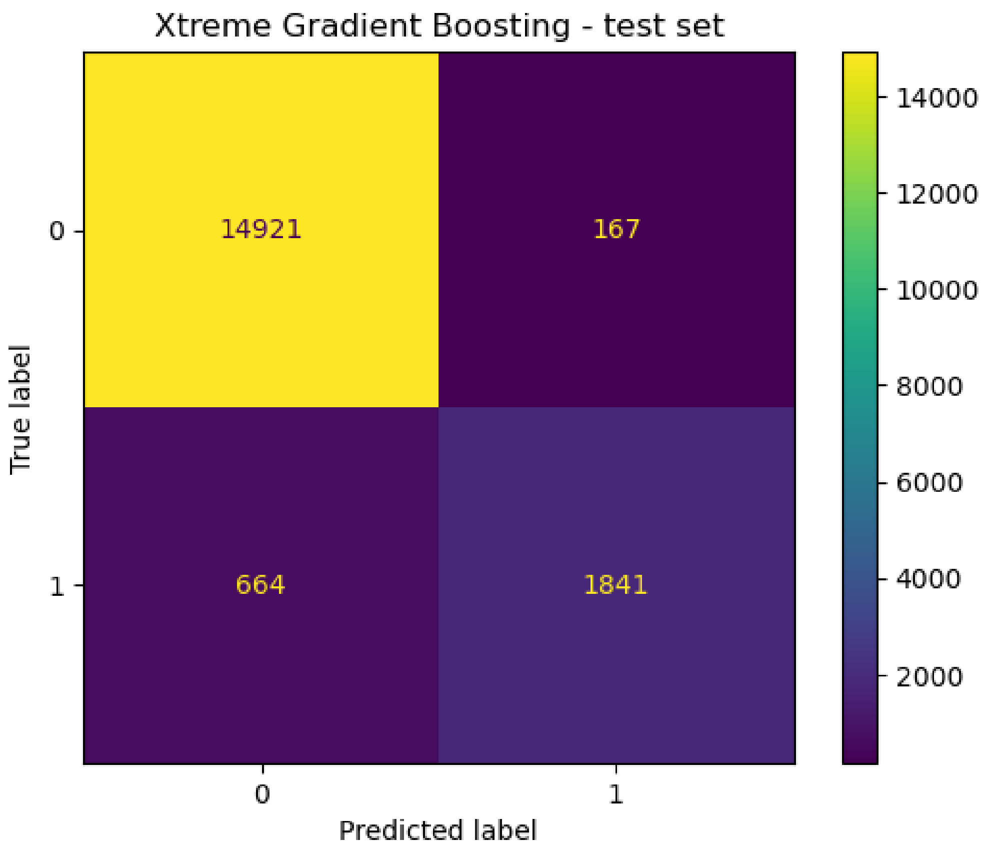
[44]:
```
y_pred_xgb = xgb_cv.best_estimator_.predict(X_test)
```

[45]:
```
print(classification_report(y_test, y_pred_xgb))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.97     15088
           1       0.92      0.73      0.82      2505

    accuracy                           0.95     17593
   macro avg       0.94      0.86      0.89     17593
weighted avg       0.95      0.95      0.95     17593
```

[46]:
```
# Compute values for confusion matrix
xgb_cm = confusion_matrix(y_test, y_pred_xgb)

# Create display of confusion matrix
xgb_disp = ConfusionMatrixDisplay(confusion_matrix=xgb_cm, display_labels=None)

# Plot confusion matrix
xgb_disp.plot()
```

```
# Display plot
plt.title('Xtreme Gradient Boosting - test set');
plt.show()
```



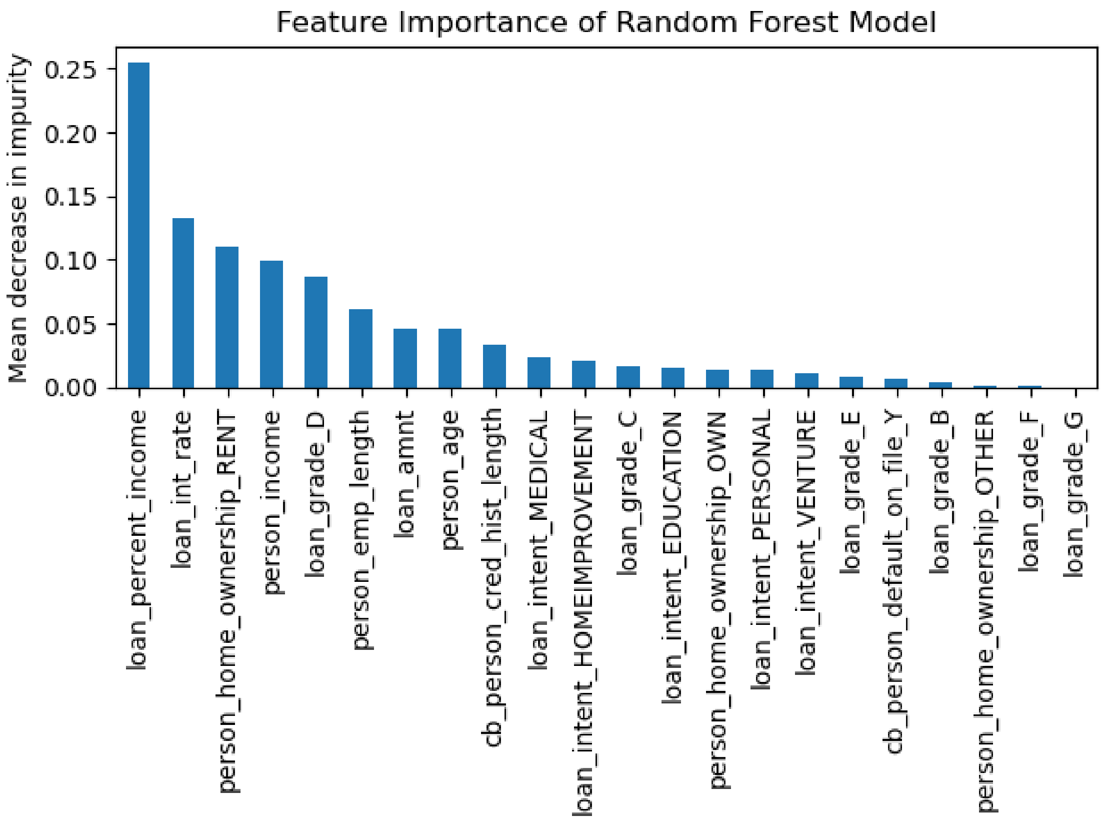
[47]:
```
#print the metrics scores
print("Accuracy:", "%.6f" % metrics.accuracy_score(y_test, y_pred_xgb))
 print("Precision:", "%.6f" % metrics.precision_score(y_test, y_pred_xgb))
 print("Recall:", "%.6f" % metrics.recall_score(y_test, y_pred_xgb))
 print("F1 Score:", "%.6f" % metrics.f1_score(y_test, y_pred_xgb))
```

```
Accuracy: 0.952765
Precision: 0.916833
Recall: 0.734930
F1 Score: 0.815865
```

From comparing the results of the models, Random Forest model is the one that gives the highest precision score and hence we select RF as the Champion model

[62]:
```
#plotting the feature importance variable to identify the most important␣
↪features of the Random Forest Model
```

```
importances = rf_cv.best_estimator_.feature_importances_
rf_importances = pd.Series(importances, index= X_test.columns).
↪sort_values(ascending=False)

fig,ax = plt.subplots()
rf_importances.plot.bar(ax=ax)
ax.set_title('Feature Importance of Random Forest Model')
ax.set_ylabel('Mean decrease in impurity')
fig.tight_layout()
```



[ ]:

```

```