Problem statement: Create a classification model to predict whether credit risk is good or bad.

In [1]: import pandas as pd import numpy as np df=pd.read_csv('credit_customers (DS).csv') In [3]: df.head(5) Out[3]: checking_status duration credit_history credit_amount savings_status employment inst purpose critical/other no known 0 <0 6.0 radio/tv 1169.0 >=7 existing credit savings 1 0<=X<200 48.0 existing paid 5951.0 <100 radio/tv 1<=X<4 critical/other 2 12.0 2096.0 <100 no checking education 4<=X<7 existing credit 3 <0 42.0 existing paid furniture/equipment 7882.0 <100 4<=X<7 delayed 4870.0 <100 1<=X<4 <0 24.0 new car previously 5 rows × 21 columns df.tail(5) In [4]: Out[4]: checking status duration credit history purpose credit_amount savings_status employment ir 995 <100 no checking 12.0 existing paid furniture/equipment 1736.0 4<=X<7 existing paid 3857.0 996 <0 30.0 used car <100 1<=X<4 997 no checking 12.0 existing paid radio/tv 804.0 <100 >=7 998 45.0 existing paid radio/tv 1845.0 <100 1<=X<4 critical/other 999 0<=X<200 45.0 4576.0 100<=X<500 used car unemployed existing credit 5 rows × 21 columns In [5]: df.shape Out[5]: (1000, 21)

1. Remove handle null values (if any).

```
df.isnull().sum()
In [6]:
Out[6]: checking_status
                                   0
        duration
                                   0
        credit_history
                                   0
        purpose
                                   0
        credit amount
                                   0
        savings_status
                                   0
                                   0
        employment
        installment commitment
                                   0
        personal status
                                   0
        other_parties
                                   0
        residence_since
                                   0
                                   0
        property_magnitude
                                   0
                                   0
        other_payment_plans
        housing
                                   0
                                   0
        existing credits
                                   0
        job
        num dependents
                                   0
        own_telephone
                                   0
        foreign worker
                                   0
        class
                                   0
        dtype: int64
In [7]:
        df.value counts()
        checking_status duration credit_history purpose
                                                                           credit_amount savings_
                  employment installment commitment personal status
                                                                             other parties reside
        nce since property magnitude age
                                              other_payment_plans housing
                                                                               existing_credits j
        ob
                                   num_dependents own_telephone foreign_worker class
        0<=X<200
                          6.0
                                    all paid
                                                     education
                                                                           433.0
                                                                                          >=1000
                     4.0
                                              female div/dep/mar
        <1
                                                                  none
                                                                                  2.0
        life insurance
                             24.0
                                   bank
                                                         rent
                                                                   1.0
                                                                                      skilled
        2.0
                         none
                                        yes
                                                         bad
                                                                   1
        no checking
                          10.0
                                    existing paid
                                                     new car
                                                                           1364.0
                                                                                          <100
        1<=X<4
                     2.0
                                              female div/dep/mar
                                                                                  4.0
                                                                  none
                                                                   1.0
                                                                                      skilled
        car
                             64.0
                                   none
                                                         own
        1.0
                                                                  1
                         yes
                                                         good
                                        yes
                          9.0
                                    existing paid
                                                     furniture/equipment 2301.0
                                                                                          100<=X<5
                               2.0
        00
                   <1
                                                        female div/dep/mar none
                                                                                            4.0
                             22.0
        life insurance
                                                         rent
                                                                   1.0
                                                                                      skilled
                                   none
        1.0
                                                         good
                                                                  1
                         none
                                         yes
                                                                           2507.0
                                                                                          500<=X<1
                                                     new car
        000
                   >=7
                               2.0
                                                        male single
                                                                             none
                                                                                            4.0
        no known property
                             51.0 none
                                                         for free 1.0
                                                                                      unskilled re
        df=df.dropna()
In [8]:
        df.shape
```

Data Preprocessing

Handling duplicate records

Out[8]: (1000, 21)

```
In [9]: df.drop_duplicates(inplace=True)
```

Identify categorical columns and performing Label Enocoding

```
In [10]: from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import LabelEncoder
```

```
In [12]: df['class'] = label_encoder.fit_transform(df['class'])
label_mapping = {0: 'good', 1: 'bad'}
df['class'] = df['class'].map(label_mapping)
```

```
In [13]: df.head(5)
```

Out[13]:

	checking_status	duration	credit_history	purpose	credit_amount	savings_status	employment	installment_c
0	1	6.0	1	6	1169.0	4	3	_
1	0	48.0	3	6	5951.0	2	0	
2	3	12.0	1	2	2096.0	2	1	
3	1	42.0	3	3	7882.0	2	1	
4	1	24.0	2	4	4870.0	2	0	

5 rows × 21 columns

Split data into training and test data.

```
In [14]: x=df.drop("class",axis=1)
    y=df["class"]
    print(type(x))
    print(type(y))
    print(x.shape)
    print(y.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
(1000, 20)
(1000,)
```

models a) Logistic Regression

```
In [16]: from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy score
In [17]: logistic_regression = LogisticRegression()
In [18]: logistic_regression.fit(x_train, y_train)
         C:\Users\HP\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: Convergenc
         eWarning: 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 (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 (http
         s://scikit-learn.org/stable/modules/linear model.html#logistic-regression)
           n iter i = check optimize result(
Out[18]:
          ▼ LogisticRegression
          LogisticRegression()
In [19]:
         logistic_regression_predictions = logistic_regression.predict(x_test)
In [20]: logistic regression accuracy = accuracy score(y test, logistic regression predictions)
In [21]: print("Logistic Regression Accuracy: ",logistic_regression_accuracy)
         Logistic Regression Accuracy: 0.73
```

b) KNN Classification

```
In [22]: from sklearn.neighbors import KNeighborsClassifier
```

```
knn classifier=KNeighborsClassifier()
In [23]:
         knn_classifier.fit(x_train,y_train)
         knn predictions = knn classifier.predict(x test)
In [24]:
         knn_accuracy = accuracy_score(y_test, knn_predictions)
In [25]: knn_accuracy
Out[25]: 0.685
In [26]: print("KNN Accuracy:",knn_accuracy)
         KNN Accuracy: 0.685
```

c) SVM Classifier with linear and rbf kernel

```
In [27]: | from sklearn.svm import SVC
In [28]: | svm_linear=SVC(kernel='linear')
         svm linear.fit(x train,y train)
         svm_pred=svm_linear.predict(x_test)
In [29]: | svm_linear_accuracy=accuracy_score(y_test,svm_pred)
In [30]: print("SVM (Linear Kernel) Accuracy:",svm_linear_accuracy)
         SVM (Linear Kernel) Accuracy: 0.71
In [31]: | svm_rbf=SVC(kernel='rbf')
         svm_rbf.fit(x_train,y_train)
         svm_rbf_pred=svm_rbf.predict(x_test)
In [32]: | svm_rbf_accuracy=accuracy_score(y_test,svm_rbf_pred)
In [33]: print("SVM (RBF Kernel) Accuracy:",svm_rbf_accuracy)
         SVM (RBF Kernel) Accuracy: 0.715
         Generate Confusion matrix and classification report for each of these models.
In [34]: from sklearn.metrics import confusion_matrix,classification_report
In [35]:
         best_accuracy = 0
         best_model = ""
```

```
9/13/23, 11:25 PM
```

```
In [36]: models = [
    ("Logistic Regression", logistic_regression_predictions),
    ("K-Nearest Neighbors", knn_predictions),
    ("SVM (Linear Kernel)", svm_pred),
    ("SVM (RBF Kernel)", svm_rbf_pred)
]
```

```
In [37]: for model_name, predictions in models:
    print("Model: ",model_name)
    confusion = confusion_matrix(y_test, predictions)
    classification_rep = classification_report(y_test, predictions)
    accuracy = (confusion[0, 0] + confusion[1, 1]) / sum(sum(confusion))

print("Confusion Matrix:")
    print(confusion)

print("\nClassification Report:")
    print(classification_rep)

print("Accuracy: ",accuracy,"\n")

if accuracy > best_accuracy:
    best_accuracy = accuracy
    best_model = model_name
```

Model: Logistic Regression

Confusion Matrix:

[[128 13] [41 18]]

Classification Report:

	precision	recall	f1-score	support
bad	0.76	0.91	0.83	141
good	0.58	0.31	0.40	59
accuracy			0.73	200
macro avg	0.67	0.61	0.61	200
weighted avg	0.71	0.73	0.70	200

Accuracy: 0.73

Model: K-Nearest Neighbors

Confusion Matrix:

[[123 18] [45 14]]

Classification Report:

	precision	recall	f1-score	support
bad	0.73	0.87	0.80	141
good	0.44	0.24	0.31	59
accuracy			0.69	200
macro avg	0.58	0.55	0.55	200
weighted avg	0.65	0.69	0.65	200

Accuracy: 0.685

Model: SVM (Linear Kernel)

Confusion Matrix:

[[116 25] [33 26]]

Classification Report:

	precision	recall	f1-score	support
bad	0.78	0.82	0.80	141
good	0.51	0.44	0.47	59
accuracy			0.71	200
macro avg	0.64	0.63	0.64	200
weighted avg	0.70	0.71	0.70	200

Accuracy: 0.71

Model: SVM (RBF Kernel)

Confusion Matrix:

[[140 1] [56 3]]

Classification Report:

support	f1-score	recall	precision	
141	0.83	0.99	0.71	bad
59	0.10	0.05	0.75	good
200	a 71			accuracy

macro avg 0.73 0.52 0.46 200 weighted avg 0.72 0.71 0.61 200

Accuracy: 0.715

In [38]: print("The model with the best accuracy is",best_model,"with an accuracy of",best_accuracy

The model with the best accuracy is Logistic Regression with an accuracy of 0.73