```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

```
# Load the dataset
df = pd.read_csv('credit_customers (DS).csv')
```

```
df.head()
```

	checking_status	duration	credit_history	purpose	credit_amount	savings_status	employment	installment_commitment	personal_statu
0	1	6.0	1	6	1169.0	4	3	4.0	
1	0	48.0	3	6	5951.0	2	0	2.0	
2	3	12.0	1	2	2096.0	2	1	2.0	
3	1	42.0	3	3	7882.0	2	1	2.0	
4	1	24.0	2	4	4870.0	2	0	3.0	

5 rows × 21 columns

```
Warning: Total number of columns (21) exceeds max_columns (20) limiting to first (20) columns.
```

```
print(df.head())
```

```
  checking_status  duration                  credit_history  \
0              <0       6.0  critical/other existing credit
1        0<=X<200      48.0                   existing paid
2     no checking      12.0  critical/other existing credit
3              <0      42.0                   existing paid
4              <0      24.0              delayed previously

              purpose  credit_amount    savings_status employment  \
0            radio/tv         1169.0  no known savings        >=7
1            radio/tv         5951.0              <100     1<=X<4
2           education         2096.0              <100     4<=X<7
3  furniture/equipment         7882.0              <100     4<=X<7
4             new car         4870.0              <100     1<=X<4

   installment_commitment     personal_status other_parties  ...  \
0                     4.0         male single          none  ...
1                     2.0  female div/dep/mar          none  ...
2                     2.0         male single          none  ...
3                     2.0         male single     guarantor  ...
4                     3.0         male single          none  ...

   property_magnitude   age  other_payment_plans   housing existing_credits  \
0         real estate  67.0                 none       own              2.0
1         real estate  22.0                 none       own              1.0
2         real estate  49.0                 none       own              1.0
3      life insurance  45.0                 none  for free              1.0
4   no known property  53.0                 none  for free              2.0

                  job num_dependents  own_telephone foreign_worker class
0            skilled            1.0            yes            yes  good
1            skilled            1.0           none            yes   bad
2  unskilled resident            2.0           none            yes  good
3            skilled            2.0           none            yes  good
4            skilled            2.0           none            yes   bad

[5 rows x 21 columns]
```

```
print(df.tail())
```

```
    checking_status  duration                  credit_history  \
995     no checking      12.0                   existing paid
996              <0      30.0                   existing paid
997     no checking      12.0                   existing paid
998              <0      45.0                   existing paid
```

```
999       0<=X<200      45.0  critical/other existing credit

                 purpose  credit_amount savings_status  employment  \
995  furniture/equipment        1736.0           <100      4<=X<7
996             used car        3857.0           <100      1<=X<4
997             radio/tv         804.0           <100         >=7
998             radio/tv        1845.0           <100      1<=X<4
999             used car        4576.0     100<=X<500  unemployed

     installment_commitment     personal_status other_parties  ...  \
995                     3.0  female div/dep/mar          none  ...
996                     4.0        male div/sep          none  ...
997                     4.0         male single          none  ...
998                     4.0         male single          none  ...
999                     3.0         male single          none  ...

     property_magnitude   age  other_payment_plans   housing existing_credits  \
995         real estate  31.0                 none       own              1.0
996      life insurance  40.0                 none       own              1.0
997                 car  38.0                 none       own              1.0
998   no known property  23.0                 none  for free              1.0
999                 car  27.0                 none       own              1.0

                      job num_dependents  own_telephone foreign_worker  \
995        unskilled resident            1.0           none            yes
996  high qualif/self emp/mgmt            1.0            yes            yes
997                   skilled            1.0           none            yes
998                   skilled            1.0            yes            yes
999                   skilled            1.0           none            yes

    class
995  good
996  good
997  good
998   bad
999  good

[5 rows x 21 columns]
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   checking_status         1000 non-null   object
 1   duration                1000 non-null   float64
 2   credit_history          1000 non-null   object
 3   purpose                 1000 non-null   object
 4   credit_amount           1000 non-null   float64
 5   savings_status          1000 non-null   object
 6   employment              1000 non-null   object
 7   installment_commitment  1000 non-null   float64
 8   personal_status         1000 non-null   object
 9   other_parties           1000 non-null   object
 10  residence_since         1000 non-null   float64
 11  property_magnitude      1000 non-null   object
 12  age                     1000 non-null   float64
 13  other_payment_plans     1000 non-null   object
 14  housing                 1000 non-null   object
 15  existing_credits        1000 non-null   float64
 16  job                     1000 non-null   object
 17  num_dependents          1000 non-null   float64
 18  own_telephone           1000 non-null   object
 19  foreign_worker          1000 non-null   object
 20  class                   1000 non-null   object
dtypes: float64(7), object(14)
memory usage: 164.2+ KB
None
```

```
# Display column names
print(df.columns)
```

```
Index(['checking_status', 'duration', 'credit_history', 'purpose',
       'credit_amount', 'savings_status', 'employment',
       'installment_commitment', 'personal_status', 'other_parties',
       'residence_since', 'property_magnitude', 'age', 'other_payment_plans',
       'housing', 'existing_credits', 'job', 'num_dependents', 'own_telephone',
       'foreign_worker', 'class'],
      dtype='object')
```

```
# Display data types of each column
print(df.dtypes)
```

```
checking_status            object
duration                  float64
credit_history             object
purpose                    object
credit_amount             float64
savings_status             object
employment                 object
installment_commitment    float64
personal_status            object
other_parties              object
residence_since           float64
property_magnitude         object
age                       float64
other_payment_plans        object
housing                    object
existing_credits          float64
job                        object
num_dependents            float64
own_telephone              object
foreign_worker             object
class                      object
dtype: object
```

```
# Get descriptive statistics
print(df.describe(include='all'))
```

```
       checking_status     duration credit_history   purpose  credit_amount  \
count             1000  1000.000000           1000      1000    1000.000000
unique               4          NaN              5        10            NaN
top        no checking          NaN  existing paid  radio/tv            NaN
freq               394          NaN            530       280            NaN
mean               NaN    20.903000            NaN       NaN    3271.258000
std                NaN    12.058814            NaN       NaN    2822.736876
min                NaN     4.000000            NaN       NaN     250.000000
25%                NaN    12.000000            NaN       NaN    1365.500000
50%                NaN    18.000000            NaN       NaN    2319.500000
75%                NaN    24.000000            NaN       NaN    3972.250000
max                NaN    72.000000            NaN       NaN   18424.000000

       savings_status employment  installment_commitment personal_status  \
count            1000       1000             1000.000000            1000
unique              5          5                     NaN               4
top              <100     1<=X<4                     NaN     male single
freq              603        339                     NaN             548
mean              NaN        NaN                2.973000             NaN
std               NaN        NaN                1.118715             NaN
min               NaN        NaN                1.000000             NaN
25%               NaN        NaN                2.000000             NaN
50%               NaN        NaN                3.000000             NaN
75%               NaN        NaN                4.000000             NaN
max               NaN        NaN                4.000000             NaN

       other_parties  ...  property_magnitude          age  \
count           1000  ...                1000  1000.000000
unique             3  ...                   4          NaN
top             none  ...                 car          NaN
freq             907  ...                 332          NaN
mean             NaN  ...                 NaN    35.546000
std              NaN  ...                 NaN    11.375469
min              NaN  ...                 NaN    19.000000
25%              NaN  ...                 NaN    27.000000
50%              NaN  ...                 NaN    33.000000
75%              NaN  ...                 NaN    42.000000
max              NaN  ...                 NaN    75.000000

        other_payment_plans housing existing_credits      job num_dependents  \
count                  1000    1000      1000.000000     1000    1000.000000
unique                    3       3              NaN        4            NaN
top                    none     own              NaN  skilled            NaN
freq                    814     713              NaN      630            NaN
mean                    NaN     NaN         1.407000      NaN       1.155000
std                     NaN     NaN         0.577654      NaN       0.362086
min                     NaN     NaN         1.000000      NaN       1.000000
25%                     NaN     NaN         1.000000      NaN       1.000000
50%                     NaN     NaN         1.000000      NaN       1.000000
75%                     NaN     NaN         2.000000      NaN       1.000000
max                     NaN     NaN         4.000000      NaN       2.000000

        own_telephone foreign_worker class
count            1000           1000  1000
```

```
unique             2              2     2
top             none            yes  good
freq             596            963   700
mean             NaN            NaN   NaN
```

```
# Check for missing values
print(df.isnull().sum())
```

```
checking_status           0
duration                  0
credit_history            0
purpose                   0
credit_amount             0
savings_status            0
employment                0
installment_commitment    0
personal_status           0
other_parties             0
residence_since           0
property_magnitude        0
age                       0
other_payment_plans       0
housing                   0
existing_credits          0
job                       0
num_dependents            0
own_telephone             0
foreign_worker            0
class                     0
dtype: int64
```

```
# Check for duplicate records
print(f"Number of duplicate rows: {df.duplicated().sum()}")
```

```
Number of duplicate rows: 0
```

```
# Check for duplicate records
print(f"Number of duplicate columns: {df.duplicated().sum()}")
```

```
Number of duplicate columns: 0
```

```
# View the distribution of the target variable
print(df['class'].value_counts())
```

```
class
good    700
bad     300
Name: count, dtype: int64
```

```
# Identify categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
```

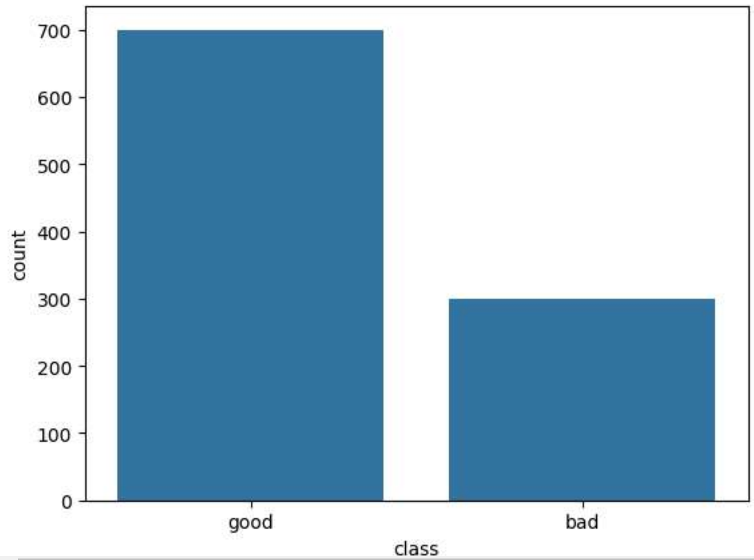
```
# Display unique values for each categorical column
for col in categorical_cols:
    print(f"Unique values in {col}: {df[col].unique()}")
```

```
Unique values in checking_status: ['<0' '0<=X<200' 'no checking' '>=200']
Unique values in credit_history: ['critical/other existing credit' 'existing paid' 'delayed previously'
 'no credits/all paid' 'all paid']
Unique values in purpose: ['radio/tv' 'education' 'furniture/equipment' 'new car' 'used car'
 'business' 'domestic appliance' 'repairs' 'other' 'retraining']
Unique values in savings_status: ['no known savings' '<100' '500<=X<1000' '>=1000' '100<=X<500']
Unique values in employment: ['>=7' '1<=X<4' '4<=X<7' 'unemployed' '<1']
Unique values in personal_status: ['male single' 'female div/dep/mar' 'male div/sep' 'male mar/wid']
Unique values in other_parties: ['none' 'guarantor' 'co applicant']
Unique values in property_magnitude: ['real estate' 'life insurance' 'no known property' 'car']
Unique values in other_payment_plans: ['none' 'bank' 'stores']
Unique values in housing: ['own' 'for free' 'rent']
Unique values in job: ['skilled' 'unskilled resident' 'high qualif/self emp/mgmt'
 'unemp/unskilled non res']
Unique values in own_telephone: ['yes' 'none']
Unique values in foreign_worker: ['yes' 'no']
Unique values in class: ['good' 'bad']
```

```
# Plot the distribution of numerical features
df.hist(figsize=(20, 20))
plt.show()
```


checking_status
duration
credit_history
purpose
credit_amount
savings_status
employment
installment_commitment
personal_status
other_parties
residence_since
property_magnitude
age
other_payment_plans
housing
existing_credits
job
num_dependents
own_telephone
foreign_worker
class

```
# Plot the distribution of the target variable
sns.countplot(x='class', data=df)
plt.show()
```




```
# Remove rows with null values
df.dropna(inplace=True)
```

```
# Verify no null values remain
print(df.isnull().sum())
```

```
checking_status           0
duration                  0
credit_history            0
purpose                   0
credit_amount             0
savings_status            0
employment                0
installment_commitment    0
personal_status           0
other_parties             0
residence_since           0
property_magnitude        0
age                       0
other_payment_plans       0
housing                   0
existing_credits          0
job                       0
num_dependents            0
own_telephone             0
foreign_worker            0
class                     0
dtype: int64
```

```
# Check for duplicate records
print(f"Number of duplicate rows: {df.duplicated().sum()}")
```

```
Number of duplicate rows: 0
```

```
# Remove duplicate records
df.drop_duplicates(inplace=True)
```

```
# Verify no duplicate records remain
print(f"Number of duplicate rows after removal: {df.duplicated().sum()}")
```

```
Number of duplicate rows after removal: 0
```

```
# Identify categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
```

```
# Apply Label Encoding
label_encoders = {}
for col in categorical_cols:
    label_encoders[col] = LabelEncoder()
    df[col] = label_encoders[col].fit_transform(df[col])


# Separate features and target variable
X = df.drop(columns=['class'])  # Independent variables
y = df['class']  # Dependent variable


# Verify shapes of X and y
print(X.shape, y.shape)
```

```
(1000, 20) (1000,)
```

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

# Verify shapes of training and test sets
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(800, 20) (200, 20) (800,) (200,)
```

```
# Logistic Regression
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train, y_train)
y_pred_log_reg = log_reg.predict(X_test)


# Evaluate Logistic Regression
print("Logistic Regression")
print(confusion_matrix(y_test, y_pred_log_reg))
print(classification_report(y_test, y_pred_log_reg))
print(f"Accuracy: {accuracy_score(y_test, y_pred_log_reg)}")
```

```
Logistic Regression
[[ 19  40]
 [ 14 127]]
              precision    recall  f1-score   support

           0       0.58      0.32      0.41        59
           1       0.76      0.90      0.82       141

    accuracy                           0.73       200
   macro avg       0.67      0.61      0.62       200
weighted avg       0.71      0.73      0.70       200

Accuracy: 0.73
```

```
print("Predictions using Logistic Regression:")
print(y_pred_log_reg)
```

```
Predictions using Logistic Regression:
[1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 0
 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 1 0 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 1 1 0
 1 1 1 0 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1
 1 1 1 0 1 1 1 0 1 1 1 0 1 1 1 0 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1
 1 1 1 1 1 1 0 0 0 1 1 0 1 1 1]
```

```
# KNN Classification
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred_knn = knn.predict(X_test)


# Evaluate KNN
print("KNN Classification")
print(confusion_matrix(y_test, y_pred_knn))
print(classification_report(y_test, y_pred_knn))
print(f"Accuracy: {accuracy_score(y_test, y_pred_knn)}")
```

```
KNN Classification
[[ 14  45]
 [ 18 123]]
              precision    recall  f1-score   support
```

```
              0       0.44      0.24      0.31        59
              1       0.73      0.87      0.80       141

       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
```

```
print("Predictions using KNN Classification:")
print(y_pred_knn)
```

```
Predictions using KNN Classification:
[1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 0 1 1
 1 1 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 1 1 1
 0 1 1 1 1 1 1 1 1 1 1 0 0 1 1 0 1 1 1 1 0 1 1 0 1 1 1 0 1 1 1 1 1 1 1 0 1
 1 0 1 1 1 1 1 0 1 1 1 0 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 0 1 1 0 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1
 1 1 1 0 1 1 1 1 0 1 1 1 1 1 1]
```

```
# SVM with Linear Kernel
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train, y_train)
y_pred_svm_linear = svm_linear.predict(X_test)
```

```
# Evaluate SVM Linear
print("SVM with Linear Kernel")
print(confusion_matrix(y_test, y_pred_svm_linear))
print(classification_report(y_test, y_pred_svm_linear))
print(f"Accuracy: {accuracy_score(y_test, y_pred_svm_linear)}")
```

```
SVM with Linear Kernel
[[ 24  35]
 [ 25 116]]
              precision    recall  f1-score   support

           0       0.49      0.41      0.44        59
           1       0.77      0.82      0.79       141

    accuracy                           0.70       200
   macro avg       0.63      0.61      0.62       200
weighted avg       0.69      0.70      0.69       200

Accuracy: 0.7
```

```
print("Predictions using SVM with Linear Kernel:")
print(y_pred_svm_linear)
```

```
Predictions using SVM with Linear Kernel:
[1 1 1 1 1 1 1 0 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 0
 1 1 0 1 1 1 1 1 1 1 0 1 1 0 1 1 0 1 0 1 0 0 1 1 0 0 1 1 0 1 1 1 1 0 1 1 1
 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 1 1 0 1 1 1 1 0 0 0 1 1 1 1 1 1 0 0 1 0 0
 1 0 1 0 1 0 1 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1
 1 1 1 0 0 1 1 0 0 1 0 0 1 1 1 0 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1
 1 1 1 1 1 1 0 0 0 1 1 0 1 1 1]
```

```
# SVM with RBF Kernel
svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(X_train, y_train)
y_pred_svm_rbf = svm_rbf.predict(X_test)
```

```
# Evaluate SVM RBF
print("SVM with RBF Kernel")
print(confusion_matrix(y_test, y_pred_svm_rbf))
print(classification_report(y_test, y_pred_svm_rbf))
print(f"Accuracy: {accuracy_score(y_test, y_pred_svm_rbf)}")
```

```
SVM with RBF Kernel
[[  3  56]
 [  1 140]]
              precision    recall  f1-score   support

           0       0.75      0.05      0.10        59
           1       0.71      0.99      0.83       141
```

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

Accuracy: 0.715
```

```
print("Predictions using SVM with RBF Kernel:")
print(y_pred_svm_rbf)
```

```
Predictions using SVM with RBF Kernel:
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

```
model_accuracies = {
    'Logistic Regression': accuracy_score(y_test, y_pred_log_reg),
    'KNN': accuracy_score(y_test, y_pred_knn),
    'SVM Linear': accuracy_score(y_test, y_pred_svm_linear),
    'SVM RBF': accuracy_score(y_test, y_pred_svm_rbf)
}
```

```
# Determine the best model
best_model = max(model_accuracies, key=model_accuracies.get)
print(f"The model with the best accuracy is {best_model} with an accuracy of {model_accuracies[best_model]}")
```

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