```
#Import Libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.model_selection import cross_val_score
```

Project Summary: KNN Model for Loan Risk Classification

Objective The goal of this project is to predict loan repayment risk using the K-Nearest Neighbors (KNN) algorithm. Our model classifies loans as either:-

- `1` (Fully Paid - Good Loan)
- `0` (Charged Off - Bad Loan)

We achieve this by analyzing a borrower characteristics and financial indicators, the model helps measures the likelyhood of loan default which helps the lender in good decison making process.

Steps

1. Data Preprocessing & Feature Selection :- Load the dataset and identify missing values. Drop irrelevant features.Encoded categorical variables. Converted our target - loan_status to binary (1 = Fully Paid, 0 = Charged Off). Scaled numerical features.Select most relevant features.

2. Train-Test Split: - Split data into training (80%) and testing (20%) sets. (ensure `loan_status` remains binary:- Just to confirm, i got errors before then decided to confirm again at this point, even though it might not be necessary).

3. KNN Model Training:- KNN classifier with `k=5` to start with. Our Evaluated model accuracy (93.93%).
   We noticed that the Recall for `Charged Off` loans was low.

4. Optimizing `k` for Better Performance:- We tuned the value of `k` (neighbors) using cross-validation, where we found 3 achieved a higher accuracy. Trained model at K=3 and our model accuracy of 94% was achieved.

```
#import data
df=pd.read_csv(r"C:\Users\User\Downloads\loan.csv")
df.head()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\975024387.py:2:
DtypeWarning: Columns (0,45) have mixed types. Specify dtype option on
```

```
import or set low_memory=False.
  df=pd.read_csv(r"C:\Users\User\Downloads\loan.csv")

    id  loan_amnt  funded_amnt  funded_amnt_inv        term
int_rate  \
0  NaN     5000.0       5000.0           4975.0   36 months   10.65%

1  NaN     2500.0       2500.0           2500.0   60 months   15.27%

2  NaN     2400.0       2400.0           2400.0   36 months   15.96%

3  NaN    10000.0      10000.0          10000.0   36 months   13.49%

4  NaN     3000.0       3000.0           3000.0   60 months   12.69%


   installment grade sub_grade                 emp_title  ...  \
0       162.87     B        B2                       NaN  ...
1        59.83     C        C4                     Ryder  ...
2        84.33     C        C5                       NaN  ...
3       339.31     C        C1       AIR RESOURCES BOARD  ...
4        67.79     B        B5  University Medical Group  ...

  last_credit_pull_d collections_12_mths_ex_med  policy_code
application_type  \
0           Jul-2017                      0.0          1.0
INDIVIDUAL
1           Oct-2016                      0.0          1.0
INDIVIDUAL
2           Jun-2017                      0.0          1.0
INDIVIDUAL
3           Apr-2016                      0.0          1.0
INDIVIDUAL
4           Jan-2017                      0.0          1.0
INDIVIDUAL

  acc_now_delinq chargeoff_within_12_mths delinq_amnt
pub_rec_bankruptcies  \
0            0.0                      0.0         0.0
0.0
1            0.0                      0.0         0.0
0.0
2            0.0                      0.0         0.0
0.0
3            0.0                      0.0         0.0
0.0
4            0.0                      0.0         0.0
0.0

  tax_liens hardship_flag
```

```
0       0.0             N
1       0.0             N
2       0.0             N
3       0.0             N
4       0.0             N

[5 rows x 56 columns]
```

```
#Contents of the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42538 entries, 0 to 42537
Data columns (total 56 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          3 non-null      object 
 1   loan_amnt                   42535 non-null  float64
 2   funded_amnt                 42535 non-null  float64
 3   funded_amnt_inv             42535 non-null  float64
 4   term                        42535 non-null  object 
 5   int_rate                    42535 non-null  object 
 6   installment                 42535 non-null  float64
 7   grade                       42535 non-null  object 
 8   sub_grade                   42535 non-null  object 
 9   emp_title                   39909 non-null  object 
 10  emp_length                  41423 non-null  object 
 11  home_ownership              42535 non-null  object 
 12  annual_inc                  42531 non-null  float64
 13  verification_status         42535 non-null  object 
 14  issue_d                     42535 non-null  object 
 15  loan_status                 42535 non-null  object 
 16  pymnt_plan                  42535 non-null  object 
 17  desc                        29240 non-null  object 
 18  purpose                     42535 non-null  object 
 19  title                       42522 non-null  object 
 20  zip_code                    42535 non-null  object 
 21  addr_state                  42535 non-null  object 
 22  dti                         42535 non-null  float64
 23  delinq_2yrs                 42506 non-null  float64
 24  earliest_cr_line            42506 non-null  object 
 25  inq_last_6mths              42506 non-null  float64
 26  mths_since_last_delinq      15609 non-null  float64
 27  mths_since_last_record      3651 non-null   float64
 28  open_acc                    42506 non-null  float64
 29  pub_rec                     42506 non-null  float64
 30  revol_bal                   42535 non-null  float64
 31  revol_util                  42445 non-null  object 
 32  total_acc                   42506 non-null  float64
 33  initial_list_status         42535 non-null  object 
```

```
 34  out_prncp                    42535 non-null  float64
 35  out_prncp_inv                42535 non-null  float64
 36  total_pymnt                  42535 non-null  float64
 37  total_pymnt_inv              42535 non-null  float64
 38  total_rec_prncp              42535 non-null  float64
 39  total_rec_int                42535 non-null  float64
 40  total_rec_late_fee           42535 non-null  float64
 41  recoveries                   42535 non-null  float64
 42  collection_recovery_fee      42535 non-null  float64
 43  last_pymnt_d                 42452 non-null  object
 44  last_pymnt_amnt              42535 non-null  float64
 45  next_pymnt_d                 2749 non-null   object
 46  last_credit_pull_d           42531 non-null  object
 47  collections_12_mths_ex_med   42390 non-null  float64
 48  policy_code                  42535 non-null  float64
 49  application_type             42535 non-null  object
 50  acc_now_delinq               42506 non-null  float64
 51  chargeoff_within_12_mths     42390 non-null  float64
 52  delinq_amnt                  42506 non-null  float64
 53  pub_rec_bankruptcies         41170 non-null  float64
 54  tax_liens                    42430 non-null  float64
 55  hardship_flag                42535 non-null  object
dtypes: float64(31), object(25)
memory usage: 18.2+ MB
```

```
# Drop irrelevant columns
df = df.drop(['id', 'desc', 'title', 'zip_code', 'next_pymnt_d'],
axis=1)

# Convert percentage column to float
df['int_rate'] = df['int_rate'].str.replace('%', '').astype(float)

# Fill missing values with 0 for numerical columns
df.fillna(0, inplace=True)

# Encode categorical columns
df = pd.get_dummies(df, columns=['term', 'grade', 'home_ownership',
'verification_status', 'purpose', 'application_type',
'initial_list_status', 'hardship_flag'], drop_first=True)

# Confirm the changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42538 entries, 0 to 42537
Data columns (total 77 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   loan_amnt                             42538 non-null  float64
 1   funded_amnt                           42538 non-null  float64
```

```
2   funded_amnt_inv                 42538 non-null  float64
3   int_rate                        42538 non-null  float64
4   installment                     42538 non-null  float64
5   sub_grade                       42538 non-null  object
6   emp_title                       42538 non-null  object
7   emp_length                      42538 non-null  object
8   annual_inc                      42538 non-null  float64
9   issue_d                         42538 non-null  object
10  loan_status                     42538 non-null  object
11  pymnt_plan                      42538 non-null  object
12  addr_state                      42538 non-null  object
13  dti                             42538 non-null  float64
14  delinq_2yrs                     42538 non-null  float64
15  earliest_cr_line                42538 non-null  object
16  inq_last_6mths                  42538 non-null  float64
17  mths_since_last_delinq          42538 non-null  float64
18  mths_since_last_record          42538 non-null  float64
19  open_acc                        42538 non-null  float64
20  pub_rec                         42538 non-null  float64
21  revol_bal                       42538 non-null  float64
22  revol_util                      42538 non-null  object
23  total_acc                       42538 non-null  float64
24  out_prncp                       42538 non-null  float64
25  out_prncp_inv                   42538 non-null  float64
26  total_pymnt                     42538 non-null  float64
27  total_pymnt_inv                 42538 non-null  float64
28  total_rec_prncp                 42538 non-null  float64
29  total_rec_int                   42538 non-null  float64
30  total_rec_late_fee              42538 non-null  float64
31  recoveries                      42538 non-null  float64
32  collection_recovery_fee         42538 non-null  float64
33  last_pymnt_d                    42538 non-null  object
34  last_pymnt_amnt                 42538 non-null  float64
35  last_credit_pull_d              42538 non-null  object
36  collections_12_mths_ex_med      42538 non-null  float64
37  policy_code                     42538 non-null  float64
38  acc_now_delinq                  42538 non-null  float64
39  chargeoff_within_12_mths        42538 non-null  float64
40  delinq_amnt                     42538 non-null  float64
41  pub_rec_bankruptcies            42538 non-null  float64
42  tax_liens                       42538 non-null  float64
43  term_ 36 months                 42538 non-null  bool
44  term_ 60 months                 42538 non-null  bool
45  grade_A                         42538 non-null  bool
46  grade_B                         42538 non-null  bool
47  grade_C                         42538 non-null  bool
48  grade_D                         42538 non-null  bool
49  grade_E                         42538 non-null  bool
50  grade_F                         42538 non-null  bool
```

```
 51  grade_G                                 42538 non-null  bool
 52  home_ownership_MORTGAGE                 42538 non-null  bool
 53  home_ownership_NONE                     42538 non-null  bool
 54  home_ownership_OTHER                    42538 non-null  bool
 55  home_ownership_OWN                      42538 non-null  bool
 56  home_ownership_RENT                     42538 non-null  bool
 57  verification_status_Not Verified        42538 non-null  bool
 58  verification_status_Source Verified     42538 non-null  bool
 59  verification_status_Verified            42538 non-null  bool
 60  purpose_car                             42538 non-null  bool
 61  purpose_credit_card                     42538 non-null  bool
 62  purpose_debt_consolidation              42538 non-null  bool
 63  purpose_educational                     42538 non-null  bool
 64  purpose_home_improvement                42538 non-null  bool
 65  purpose_house                           42538 non-null  bool
 66  purpose_major_purchase                  42538 non-null  bool
 67  purpose_medical                         42538 non-null  bool
 68  purpose_moving                          42538 non-null  bool
 69  purpose_other                           42538 non-null  bool
 70  purpose_renewable_energy                42538 non-null  bool
 71  purpose_small_business                  42538 non-null  bool
 72  purpose_vacation                        42538 non-null  bool
 73  purpose_wedding                         42538 non-null  bool
 74  application_type_INDIVIDUAL             42538 non-null  bool
 75  initial_list_status_f                   42538 non-null  bool
 76  hardship_flag_N                         42538 non-null  bool
dtypes: bool(34), float64(32), object(11)
memory usage: 15.3+ MB
```

```
# Check for missing values
missing_values = df.isnull().sum()
missing_values[missing_values > 0]
```

```
Series([], dtype: int64)
```

```
df.isna().sum()
```

```
loan_amnt                       0
funded_amnt                     0
funded_amnt_inv                 0
int_rate                        0
installment                     0
                               ..
purpose_vacation                0
purpose_wedding                 0
application_type_INDIVIDUAL     0
initial_list_status_f           0
hardship_flag_N                 0
Length: 77, dtype: int64
```

```
#What is our target variable? Loan status
# Check unique values in loan_status
df['loan_status'].value_counts()
```

```
loan_status
Fully Paid                                                   34116
Charged Off                                                   5670
Does not meet the credit policy. Status:Fully Paid            1988
Does not meet the credit policy. Status:Charged Off            761
0                                                                3
Name: count, dtype: int64
```

```
"""
New Binary Classification:
"Good Loan" (1) → Fully Paid
"Bad Loan" (0) → Charged Off
We'll remove "Does not meet the credit policy" and the unknown "0"
values since they might add noise.
"""
```

```
'\nNew Binary Classification:\n"Good Loan" (1) → Fully Paid\n"Bad
Loan" (0) → Charged Off\nWe\'ll remove "Does not meet the credit
policy" and the unknown "0" values since they might add noise.\n'
```

```
# Remove unwanted categories
df = df[df['loan_status'].isin(['Fully Paid', 'Charged Off'])]

# Convert loan_status to binary (1 = Fully Paid, 0 = Charged Off)
df['loan_status'] = df['loan_status'].map({'Fully Paid': 1, 'Charged
Off': 0})

# Verify the changes
df['loan_status'].value_counts()
```

```
loan_status
1    34116
0     5670
Name: count, dtype: int64
```

```
df.head()
```

```
   loan_amnt  funded_amnt  funded_amnt_inv  int_rate  installment
sub_grade  \
0     5000.0       5000.0           4975.0     10.65       162.87
B2
1     2500.0       2500.0           2500.0     15.27        59.83
C4
2     2400.0       2400.0           2400.0     15.96        84.33
C5
3    10000.0      10000.0          10000.0     13.49       339.31
C1
```

```
4     3000.0       3000.0           3000.0     12.69        67.79
B5

                   emp_title emp_length  annual_inc   issue_d  ...  \
0                          0  10+ years     24000.0  Dec-2011  ...
1                      Ryder   < 1 year     30000.0  Dec-2011  ...
2                          0  10+ years     12252.0  Dec-2011  ...
3       AIR RESOURCES BOARD  10+ years     49200.0  Dec-2011  ...
4  University Medical Group     1 year     80000.0  Dec-2011  ...

   purpose_medical purpose_moving purpose_other
purpose_renewable_energy  \
0            False          False         False
False
1            False          False         False
False
2            False          False         False
False
3            False          False          True
False
4            False          False          True
False

   purpose_small_business purpose_vacation  purpose_wedding  \
0                   False            False            False
1                   False            False            False
2                    True            False            False
3                   False            False            False
4                   False            False            False

   application_type_INDIVIDUAL  initial_list_status_f  hardship_flag_N

0                         True                   True             True

1                         True                   True             True

2                         True                   True             True

3                         True                   True             True

4                         True                   True             True


[5 rows x 77 columns]

# Check for missing values
missing_values = df.isnull().sum()
missing_values[missing_values > 0]

Series([], dtype: int64)
```

```
df['emp_title'].value_counts()
```

```
emp_title
0                                  2467
US Army                             134
Bank of America                     109
IBM                                  66
AT&T                                 60
                                   ...
duncan tire co                         1
Bright House Networks                  1
Florida Power & Light Company          1
Telefutura Net                         1
Evergreen Center                       1
Name: count, Length: 28863, dtype: int64
```

```
#Why should we drop emp_title column
"""
Too Many Unique Values → Each job title is unique, making it hard to generalize.
High Cardinality → One-hot encoding would create thousands of columns.
Doesn't Strongly Affect Loan Status → A person's job title alone isn't a strong predictor of loan default.
"""
```

```
"\nToo Many Unique Values → Each job title is unique, making it hard to generalize.\nHigh Cardinality → One-hot encoding would create thousands of columns.\nDoesn't Strongly Affect Loan Status → A person's job title alone isn't a strong predictor of loan default.\n"
```

```
# Drop emp_title since it has too many unique values
df = df.drop(['emp_title'], axis=1)

# Verify the change
df.shape
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 39786 entries, 0 to 39785
Data columns (total 76 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   loan_amnt                             39786 non-null  float64
 1   funded_amnt                           39786 non-null  float64
 2   funded_amnt_inv                       39786 non-null  float64
 3   int_rate                              39786 non-null  float64
 4   installment                           39786 non-null  float64
 5   sub_grade                             39786 non-null  object 
 6   emp_length                            39786 non-null  object 
 7   annual_inc                            39786 non-null  float64
```

```
8   issue_d                                39786 non-null  object
9   loan_status                            39786 non-null  int64
10  pymnt_plan                             39786 non-null  object
11  addr_state                             39786 non-null  object
12  dti                                    39786 non-null  float64
13  delinq_2yrs                            39786 non-null  float64
14  earliest_cr_line                       39786 non-null  object
15  inq_last_6mths                         39786 non-null  float64
16  mths_since_last_delinq                 39786 non-null  float64
17  mths_since_last_record                 39786 non-null  float64
18  open_acc                               39786 non-null  float64
19  pub_rec                                39786 non-null  float64
20  revol_bal                              39786 non-null  float64
21  revol_util                             39786 non-null  object
22  total_acc                              39786 non-null  float64
23  out_prncp                              39786 non-null  float64
24  out_prncp_inv                          39786 non-null  float64
25  total_pymnt                            39786 non-null  float64
26  total_pymnt_inv                        39786 non-null  float64
27  total_rec_prncp                        39786 non-null  float64
28  total_rec_int                          39786 non-null  float64
29  total_rec_late_fee                     39786 non-null  float64
30  recoveries                             39786 non-null  float64
31  collection_recovery_fee                39786 non-null  float64
32  last_pymnt_d                           39786 non-null  object
33  last_pymnt_amnt                        39786 non-null  float64
34  last_credit_pull_d                     39786 non-null  object
35  collections_12_mths_ex_med             39786 non-null  float64
36  policy_code                            39786 non-null  float64
37  acc_now_delinq                         39786 non-null  float64
38  chargeoff_within_12_mths               39786 non-null  float64
39  delinq_amnt                            39786 non-null  float64
40  pub_rec_bankruptcies                   39786 non-null  float64
41  tax_liens                              39786 non-null  float64
42  term_ 36 months                        39786 non-null  bool
43  term_ 60 months                        39786 non-null  bool
44  grade_A                                39786 non-null  bool
45  grade_B                                39786 non-null  bool
46  grade_C                                39786 non-null  bool
47  grade_D                                39786 non-null  bool
48  grade_E                                39786 non-null  bool
49  grade_F                                39786 non-null  bool
50  grade_G                                39786 non-null  bool
51  home_ownership_MORTGAGE                39786 non-null  bool
52  home_ownership_NONE                    39786 non-null  bool
53  home_ownership_OTHER                   39786 non-null  bool
54  home_ownership_OWN                     39786 non-null  bool
55  home_ownership_RENT                    39786 non-null  bool
56  verification_status_Not Verified       39786 non-null  bool
```

```
 57  verification_status_Source Verified  39786 non-null  bool
 58  verification_status_Verified         39786 non-null  bool
 59  purpose_car                          39786 non-null  bool
 60  purpose_credit_card                  39786 non-null  bool
 61  purpose_debt_consolidation           39786 non-null  bool
 62  purpose_educational                  39786 non-null  bool
 63  purpose_home_improvement             39786 non-null  bool
 64  purpose_house                        39786 non-null  bool
 65  purpose_major_purchase               39786 non-null  bool
 66  purpose_medical                      39786 non-null  bool
 67  purpose_moving                       39786 non-null  bool
 68  purpose_other                        39786 non-null  bool
 69  purpose_renewable_energy             39786 non-null  bool
 70  purpose_small_business               39786 non-null  bool
 71  purpose_vacation                     39786 non-null  bool
 72  purpose_wedding                      39786 non-null  bool
 73  application_type_INDIVIDUAL          39786 non-null  bool
 74  initial_list_status_f                39786 non-null  bool
 75  hardship_flag_N                      39786 non-null  bool
dtypes: bool(34), float64(32), int64(1), object(9)
memory usage: 14.3+ MB
```

```
# Ensure columns are strings before replacing '%'
df['int_rate'] = df['int_rate'].astype(str).str.replace('%', '',
regex=True)
df['revol_util'] = df['revol_util'].astype(str).str.replace('%', '',
regex=True)

# Convert to float (ignoring errors)
df['int_rate'] = pd.to_numeric(df['int_rate'], errors='coerce')
df['revol_util'] = pd.to_numeric(df['revol_util'], errors='coerce')

# Fill any remaining missing values with the median
df['int_rate'].fillna(df['int_rate'].median(), inplace=True)
df['revol_util'].fillna(df['revol_util'].median(), inplace=True)

# Confirm the data types
df[['int_rate', 'revol_util']].dtypes
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\3353092874.py:10:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.
```

```
  df['int_rate'].fillna(df['int_rate'].median(), inplace=True)
C:\Users\User\AppData\Local\Temp\ipykernel_1768\3353092874.py:11:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['revol_util'].fillna(df['revol_util'].median(), inplace=True)

int_rate      float64
revol_util    float64
dtype: object

from sklearn.preprocessing import StandardScaler

# Select only numerical features (EXCLUDE loan_status)
numerical_features =
df.drop(columns=['loan_status']).select_dtypes(include=['float64',
'int64']).columns

# Scale only numerical features
scaler = StandardScaler()
df[numerical_features] = scaler.fit_transform(df[numerical_features])

# Verify that loan_status remains unchanged
df['loan_status'].unique()

array([1, 0], dtype=int64)

df.shape

(39786, 76)

df['sub_grade'].value_counts()

sub_grade
B3    2924
A4    2886
A5    2742
B5    2709
B4    2514
C1    2142
B2    2058
```

```
C2    2014
B1    1830
A3    1810
C3    1529
A2    1508
D2    1352
C4    1238
C5    1188
D3    1178
A1    1139
D4     986
D1     931
D5     878
E1     768
E2     659
E3     556
E4     455
E5     420
F1     329
F2     251
F3     187
F4     169
F5     118
G1     105
G2      78
G4      56
G3      49
G5      30
Name: count, dtype: int64
```

```
# Create an ordinal encoder
encoder =
OrdinalEncoder(categories=[sorted(df['sub_grade'].unique())])

# Transform the sub_grade column
df.loc[:, 'sub_grade'] = encoder.fit_transform(df[['sub_grade']])

# Convert to integer (optional)
df['sub_grade'] = df['sub_grade'].astype(int)

# Verify encoding
df[['sub_grade']].head()
```

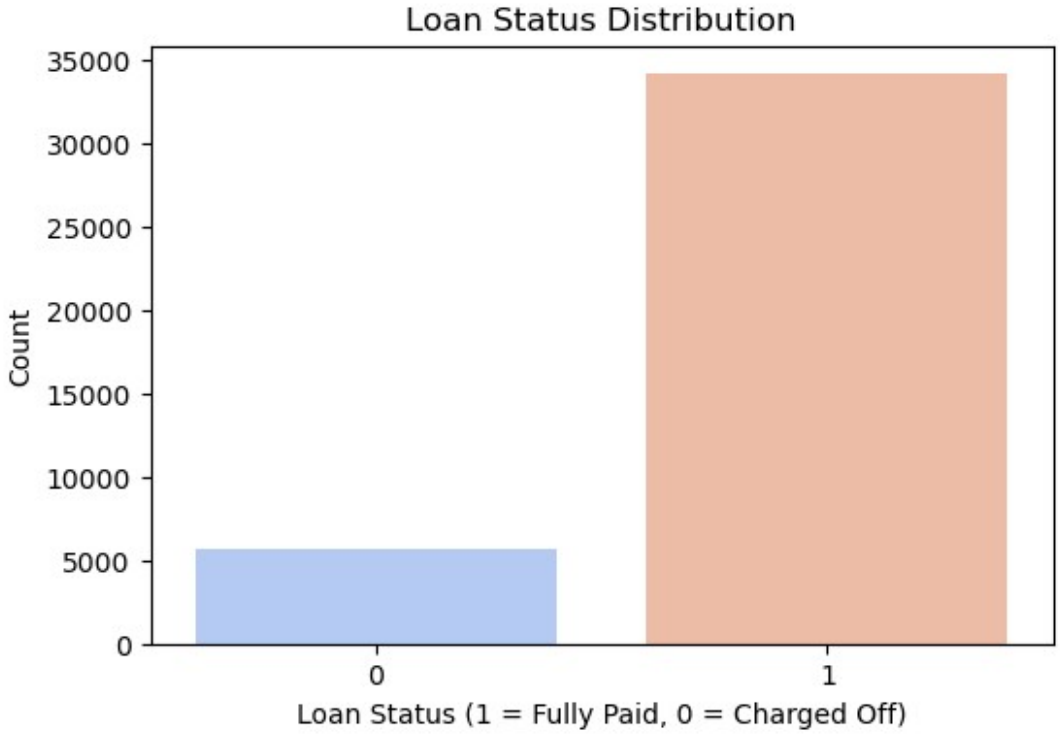
```
   sub_grade
0          6
1         13
2         14
3         10
4          9
```

```
# Count unique sub_grade values after encoding
df['sub_grade'].nunique(), df['sub_grade'].unique()
```

```
(35,
 array([ 6, 13, 14, 10,  9,  3, 20, 26, 12,  5, 15,  0,  7,  8, 11,
16,  2,
         4, 19,  1, 23, 17, 18, 27, 22, 28, 25, 24, 33, 21, 32, 31,
30, 29,
        34]))
```

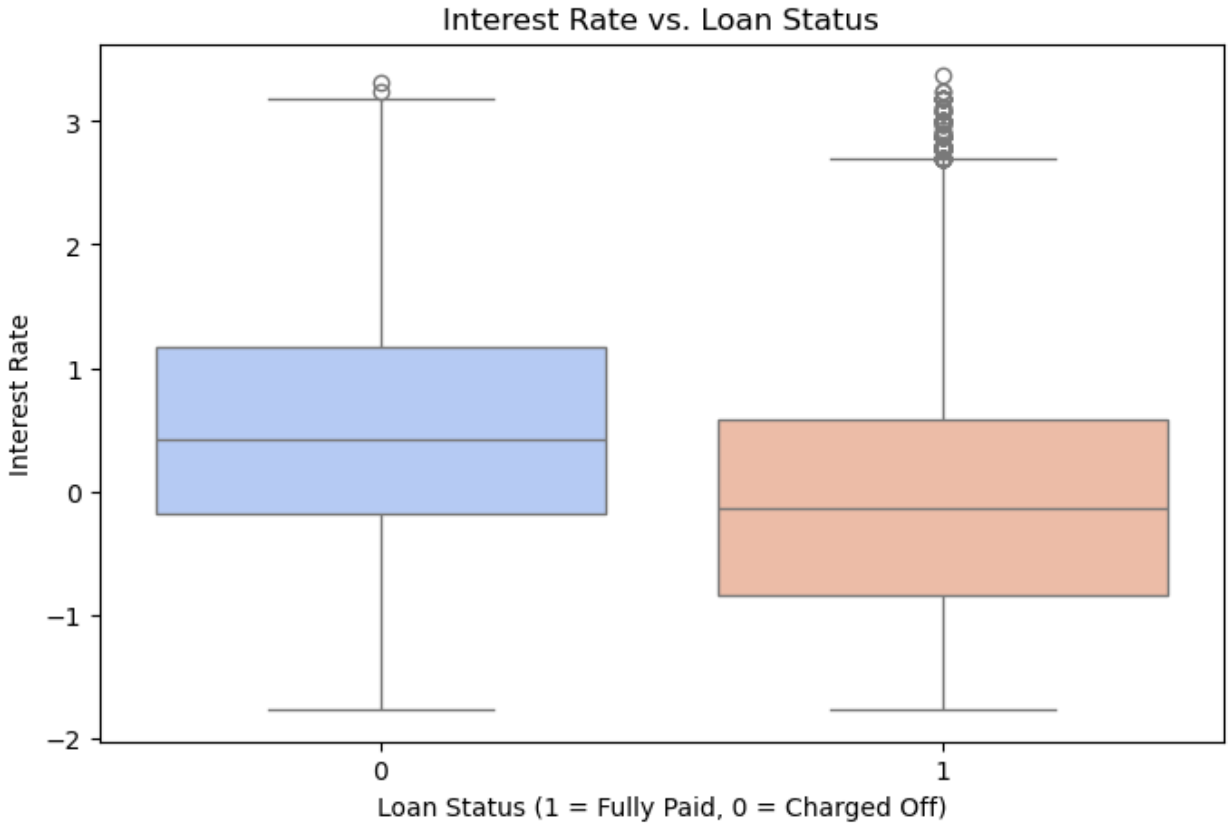
```
#Lets Check Class Imbalance in loan_status
# Plot loan_status distribution
plt.figure(figsize=(6, 4))
sns.countplot(x=df['loan_status'], palette='coolwarm')
plt.title('Loan Status Distribution')
plt.xlabel('Loan Status (1 = Fully Paid, 0 = Charged Off)')
plt.ylabel('Count')
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\1444407057.py:4:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x=df['loan_status'], palette='coolwarm')
```



```
#Check int_rate vs. loan_status
plt.figure(figsize=(8, 5))
sns.boxplot(x=df['loan_status'], y=df['int_rate'], palette='coolwarm')
plt.title('Interest Rate vs. Loan Status')
plt.xlabel('Loan Status (1 = Fully Paid, 0 = Charged Off)')
plt.ylabel('Interest Rate')
plt.show()
```

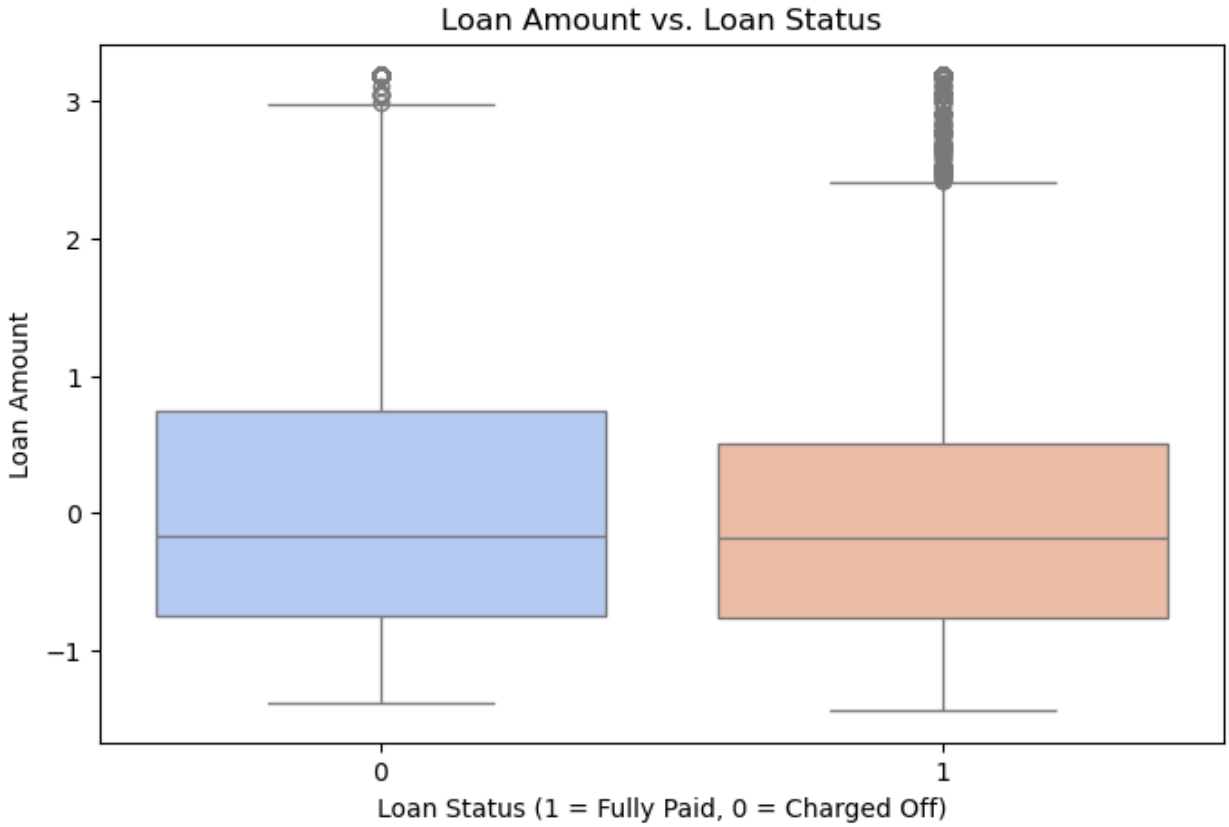
```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\740979906.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x=df['loan_status'], y=df['int_rate'],
palette='coolwarm')
```




```
#Check loan_amnt vs. loan_status
plt.figure(figsize=(8, 5))
sns.boxplot(x=df['loan_status'], y=df['loan_amnt'],
palette='coolwarm')
plt.title('Loan Amount vs. Loan Status')
plt.xlabel('Loan Status (1 = Fully Paid, 0 = Charged Off)')
```

```
plt.ylabel('Loan Amount')
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\3011782116.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x=df['loan_status'], y=df['loan_amnt'],
palette='coolwarm')
```




```
# Convert 'emp_length' to numerical values
df['emp_length'] = df['emp_length'].replace({
    '10+ years': 10,
    '9 years': 9,
    '8 years': 8,
    '7 years': 7,
    '6 years': 6,
    '5 years': 5,
    '4 years': 4,
    '3 years': 3,
    '2 years': 2,
```

```
    '1 year': 1,
    '< 1 year': 0,
    'n/a': 0  # Treat 'n/a' as 0 (no experience)
}).astype(int)

# Verify changes
df['emp_length'].unique()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_1768\715201066.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and
will be removed in a future version. To retain the old behavior,
explicitly call `result.infer_objects(copy=False)`. To opt-in to the
future behavior, set `pd.set_option('future.no_silent_downcasting',
True)`
  df['emp_length'] = df['emp_length'].replace({
```

```
array([10,  0,  1,  3,  8,  9,  4,  5,  6,  2,  7])
```

```
#Check Correlations
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), cmap='coolwarm', annot=False)
plt.title('Feature Correlation Heatmap')
plt.show()
```

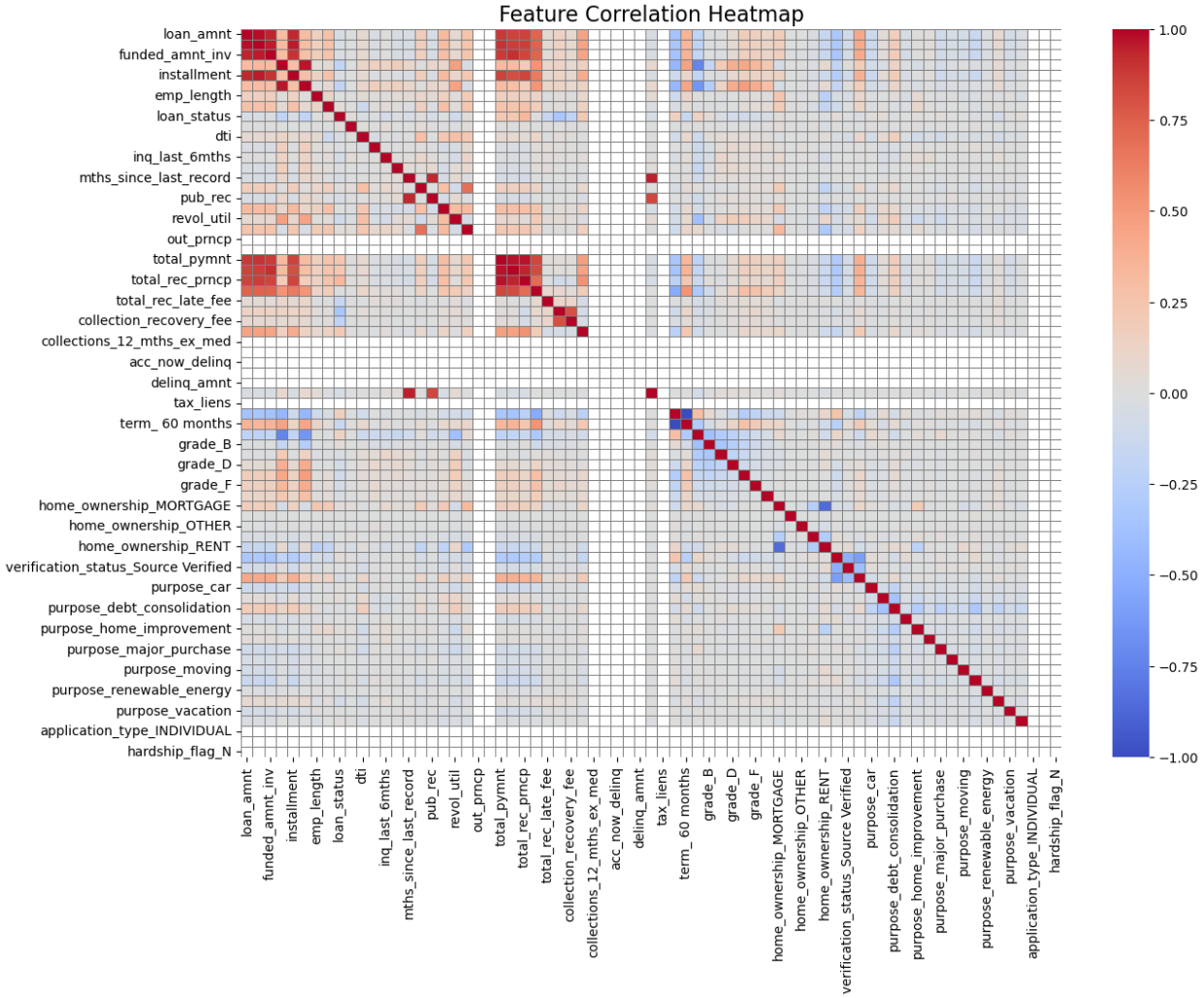
```
---------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[363], line 3
      1 #Check Correlations
      2 plt.figure(figsize=(12, 8))
----> 3 sns.heatmap(df.corr(), cmap='coolwarm', annot=False)
      4 plt.title('Feature Correlation Heatmap')
      5 plt.show()

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:11049, in
DataFrame.corr(self, method, min_periods, numeric_only)
  11047 cols = data.columns
  11048 idx = cols.copy()
> 11049 mat = data.to_numpy(dtype=float, na_value=np.nan, copy=False)
  11051 if method == "pearson":
  11052     correl = libalgos.nancorr(mat, minp=min_periods)

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:1993, in
DataFrame.to_numpy(self, dtype, copy, na_value)
   1991 if dtype is not None:
   1992     dtype = np.dtype(dtype)
-> 1993 result = self._mgr.as_array(dtype=dtype, copy=copy,
na_value=na_value)
   1994 if result.dtype is not dtype:
```

```
   1995     result = np.asarray(result, dtype=dtype)

File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1694, in BlockManager.as_array(self, dtype, copy,
na_value)
   1692         arr.flags.writeable = False
   1693 else:
-> 1694     arr = self._interleave(dtype=dtype, na_value=na_value)
   1695     # The underlying data was copied within _interleave, so no
need
   1696     # to further copy if copy=True or setting na_value
   1698 if na_value is lib.no_default:

File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1753, in BlockManager._interleave(self, dtype, na_value)
   1751     else:
   1752         arr = blk.get_values(dtype)
-> 1753     result[rl.indexer] = arr
   1754     itemmask[rl.indexer] = 1
   1756 if not itemmask.all():

ValueError: could not convert string to float: 'Dec-2011'

<Figure size 1200x800 with 0 Axes>

# Find non-numeric columns
df.dtypes[df.dtypes == 'object']

issue_d                 object
pymnt_plan              object
addr_state              object
earliest_cr_line        object
last_pymnt_d            object
last_credit_pull_d      object
dtype: object

"""
Drop Unnecessary Columns
Some of these columns won't help KNN and should be removed:

Dates → issue_d, earliest_cr_line, last_pymnt_d, last_credit_pull_d
Single-Value Columns (Not useful) → pymnt_plan (Usually all "n")
"""

df = df.drop(columns=['issue_d', 'earliest_cr_line', 'last_pymnt_d',
'last_credit_pull_d', 'pymnt_plan'])

#Encode addr_state (State of Borrower)
# Encode state into numbers
encoder = LabelEncoder()
df['addr_state'] = encoder.fit_transform(df['addr_state'])
```

```
# Verify changes
df['addr_state'].unique()
```

```
array([ 3, 10, 14,  4, 36, 27, 42, 44, 24,  6, 43,  9, 33, 37, 23, 30,
17,
       34, 39, 38, 18, 19, 46, 47,  1,  5, 16, 32,  0, 20, 48, 45, 22,
7,
       40, 29,  2, 31, 26, 11, 49, 35,  8, 25, 41, 12, 28, 13, 15,
21])
```

```
#Heatmap
plt.figure(figsize=(14, 10))  # Bigger figure size
sns.heatmap(df.corr(), cmap='coolwarm', annot=False, linewidths=0.5,
linecolor='gray', vmin=-1, vmax=1)
plt.title('Feature Correlation Heatmap', fontsize=16)
plt.show()
```



```
"""
Identify Important Features
Since KNN is distance-based, we want to:
1. Keep features that correlate well with loan_status.
2. Remove highly correlated features (to avoid redundancy).
3. Avoid unnecessary columns that add noise.
"""
```

```
'\nIdentify Important Features\nSince KNN is distance-based, we want to:\n1. Keep features that correlate well with loan_status.\n2. Remove highly correlated features (to avoid redundancy).\n3. Avoid unnecessary columns that add noise.\n'
```

```
# Check correlation of features with loan_status
correlation = df.corr()['loan_status'].sort_values(ascending=False)
correlation.head(20)
```

```
loan_status                 1.000000
total_rec_prncp             0.331227
total_pymnt                 0.233497
total_pymnt_inv             0.230702
last_pymnt_amnt             0.215818
term_ 36 months             0.149151
grade_A                     0.138053
term_ 60 months            -0.149151
total_rec_late_fee         -0.160817
sub_grade                  -0.194928
int_rate                   -0.197918
collection_recovery_fee    -0.207303
recoveries                 -0.339278
Name: loan_status, dtype: float64
```

```
# Set correlation threshold (keep features with |correlation| > 0.1)
corr_threshold = 0.1

# Compute correlations with loan_status
correlation = df.corr()['loan_status'].sort_values(ascending=False)

# Select features above the threshold
selected_features = correlation[abs(correlation) >
corr_threshold].index.tolist()

# Keep only selected features in the dataset
df = df[selected_features]

# Verify final selected features
df.head()
```

```
   loan_status  total_rec_prncp  total_pymnt  total_pymnt_inv  \
0            1        -0.679719    -0.694605        -0.640585
1            0        -1.315777    -1.223512        -1.171890
```

```
2             1        -1.043698    -1.006311        -0.952376
3             1         0.020239     0.000121         0.064768
4             1        -0.959703    -0.890547        -0.835380

   last_pymnt_amnt  term_ 36 months  grade_A  term_ 60 months  \
0        -0.564321             True    False            False
1        -0.576015            False    False             True
2        -0.456679             True    False            False
3        -0.522492             True    False            False
4        -0.587799            False    False             True

   total_rec_late_fee  sub_grade  int_rate  collection_recovery_fee  \
0           -0.187702          6 -0.369659                -0.084512
1           -0.187702         13  0.869805                -0.077178
2           -0.187702         14  1.054919                -0.084512
3            2.105899         10  0.392262                -0.084512
4           -0.187702          9  0.177637                -0.084512

   recoveries
0   -0.138315
1    0.035818
2   -0.138315
3   -0.138315
4   -0.138315

df.shape

df.columns

Index(['loan_status', 'total_rec_prncp', 'total_pymnt',
'total_pymnt_inv',
       'last_pymnt_amnt', 'term_ 36 months', 'grade_A', 'term_ 60
months',
       'total_rec_late_fee', 'sub_grade', 'int_rate',
       'collection_recovery_fee', 'recoveries'],
      dtype='object')

# Show unique values in loan_status
df['loan_status'].unique()

array([1, 0], dtype=int64)


# Define features (X) and target (y)
X = df.drop(columns=['loan_status'])  # Features (all except
loan_status)
y = df['loan_status']  # Target (1 = Fully Paid, 0 = Charged Off)

# Split into train (80%) and test (20%) sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

```
# Verify the shape of train and test sets
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((31828, 12), (7958, 12), (31828,), (7958,))
```

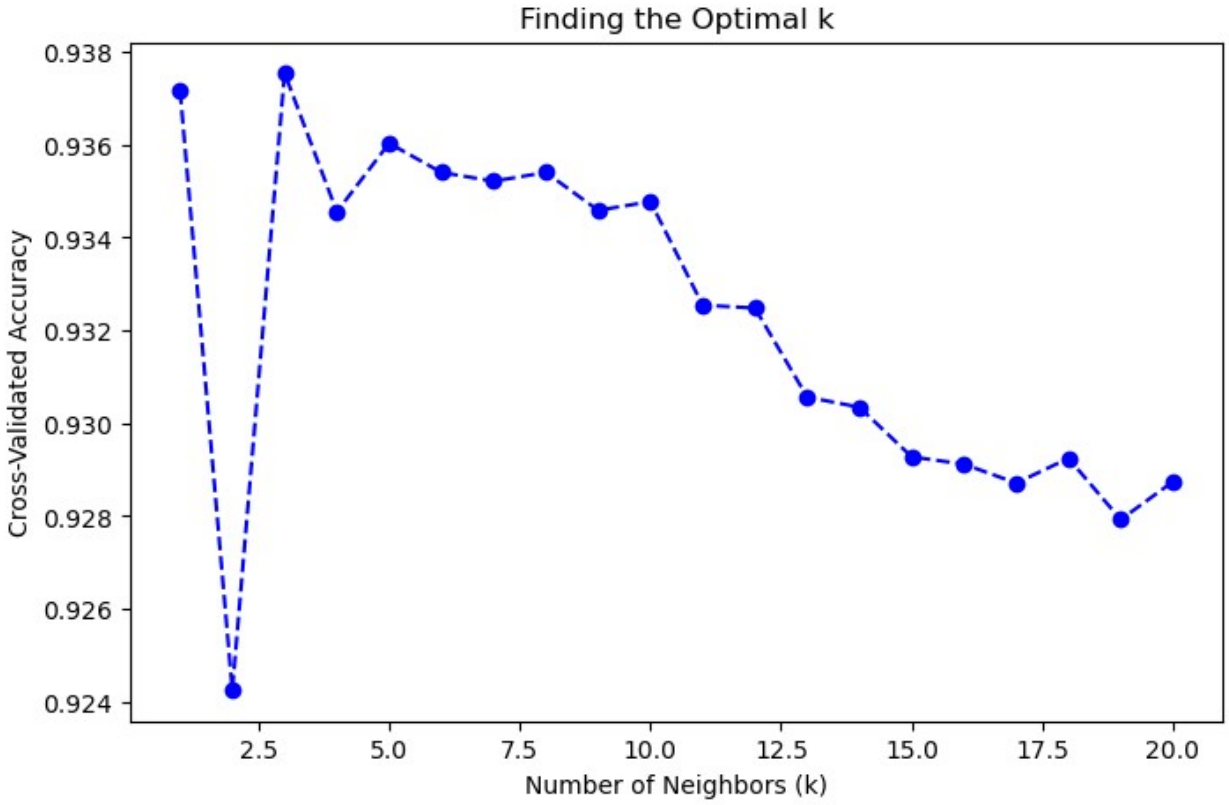
```
#Train the KNN Model
# Initialize KNN with k=5 (default)
knn = KNeighborsClassifier(n_neighbors=5)

# Train the model
knn.fit(X_train, y_train)

# Make predictions on the test set
y_pred = knn.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'KNN Model Accuracy: {accuracy:.4f}')

# Print classification report
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

# Confusion matrix
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
KNN Model Accuracy: 0.9393

Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.64      0.75      1109
           1       0.94      0.99      0.97      6849

    accuracy                           0.94      7958
   macro avg       0.92      0.81      0.86      7958
weighted avg       0.94      0.94      0.93      7958


Confusion Matrix:
 [[ 710  399]
 [  84 6765]]
```

```
#Tune k for Better Performance
# Try different values of k
k_values = range(1, 21)  # Test k from 1 to 20
cv_scores = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
```

```
    scores = cross_val_score(knn, X_train, y_train, cv=5,
scoring='accuracy')
    cv_scores.append(scores.mean())

# Find the best k
best_k = k_values[np.argmax(cv_scores)]
print(f'Best k: {best_k}')

# Plot k vs. accuracy
plt.figure(figsize=(8, 5))
plt.plot(k_values, cv_scores, marker='o', linestyle='dashed',
color='b')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Finding the Optimal k')
plt.show()
```

```
Best k: 3
```




```
#Train KNN with k=3
# Train the optimized KNN model
knn_optimized = KNeighborsClassifier(n_neighbors=3)
knn_optimized.fit(X_train, y_train)
```

```python
# Make predictions
y_pred_optimized = knn_optimized.predict(X_test)

# Evaluate the model
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

accuracy = accuracy_score(y_test, y_pred_optimized)
print(f'Optimized KNN Model Accuracy (k=3): {accuracy:.4f}')

print("\nClassification Report:\n", classification_report(y_test,
y_pred_optimized))
print("\nConfusion Matrix:\n", confusion_matrix(y_test,
y_pred_optimized))
```

```
Optimized KNN Model Accuracy (k=3): 0.9407

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.66      0.76      1109
           1       0.95      0.99      0.97      6849

    accuracy                           0.94      7958
   macro avg       0.91      0.82      0.86      7958
weighted avg       0.94      0.94      0.94      7958


Confusion Matrix:
 [[ 737  372]
 [ 100 6749]]
```