```python
# Importing the libraries
import pandas as pd
import torch
import torch.nn as nn
import torch.optim as optim
import time
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.impute import SimpleImputer
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

data = pd.read_csv('bank_data.csv')
data.head()
```

```
   Unnamed: 0  id  dependents      education self_employed
income_annual  \
0           0   1           2       Graduate            No
9600000.0
1           1   2           0   Not Graduate           Yes
4100000.0
2           2   3           3       Graduate            No
9100000.0
3           3   4           3       Graduate            No
8200000.0
4           4   5           5   Not Graduate           Yes
9800000.0

   loan_amount  loan_term  cibil_score  residential_assets_value  \
0     29900000         12          778                   2400000
1     12200000          8          417                   2700000
2     29700000         20          506                   7100000
3     30700000          8          467                  18200000
4     24200000         20          382                  12400000

   commercial_assets_value  luxury_assets_value  bank_asset_value
loan_status
0                 17600000             22700000               NaN
Approved
1                  2200000              8800000         3300000.0
Rejected
2                  4500000             33300000        12800000.0
Rejected
3                  3300000             23300000         7900000.0
Rejected
4                  8200000             29400000         5000000.0
Rejected
```

```python
#check for NaN values
data.isnull().sum()
```

```
Unnamed: 0                    0
id                            0
dependents                    0
education                     0
self_employed                 0
income_annual               213
loan_amount                   0
loan_term                     0
cibil_score                   0
residential_assets_value      0
commercial_assets_value       0
luxury_assets_value           0
bank_asset_value            341
loan_status                   0
dtype: int64
```

```python
# Calculate descriptive statistics for numerical columns
numerical_descriptive_stats = data.describe()
numerical_descriptive_stats
```

```
        Unnamed: 0           id   dependents  income_annual
loan_amount  \
count  4268.000000  4268.000000  4268.000000   4.055000e+03
4.268000e+03
mean   2133.500000  2134.500000     2.499063   5.049420e+06
1.513004e+07
std    1232.209804  1232.209804     1.695954   2.799091e+06
9.041673e+06
min       0.000000     1.000000     0.000000   2.000000e+05
3.000000e+05
25%    1066.750000  1067.750000     1.000000   2.700000e+06
7.700000e+06
50%    2133.500000  2134.500000     3.000000   5.100000e+06
1.450000e+07
75%    3200.250000  3201.250000     4.000000   7.500000e+06
2.150000e+07
max    4267.000000  4268.000000     5.000000   9.900000e+06
3.950000e+07

         loan_term  cibil_score  residential_assets_value  \
count  4268.000000  4268.000000              4.268000e+03
mean     10.900656   599.934396              7.470197e+06
std       5.709840   172.450571              6.502476e+06
min       2.000000   300.000000             -1.000000e+05
25%       6.000000   453.000000              2.200000e+06
50%      10.000000   600.000000              5.600000e+06
75%      16.000000   748.000000              1.130000e+07
```

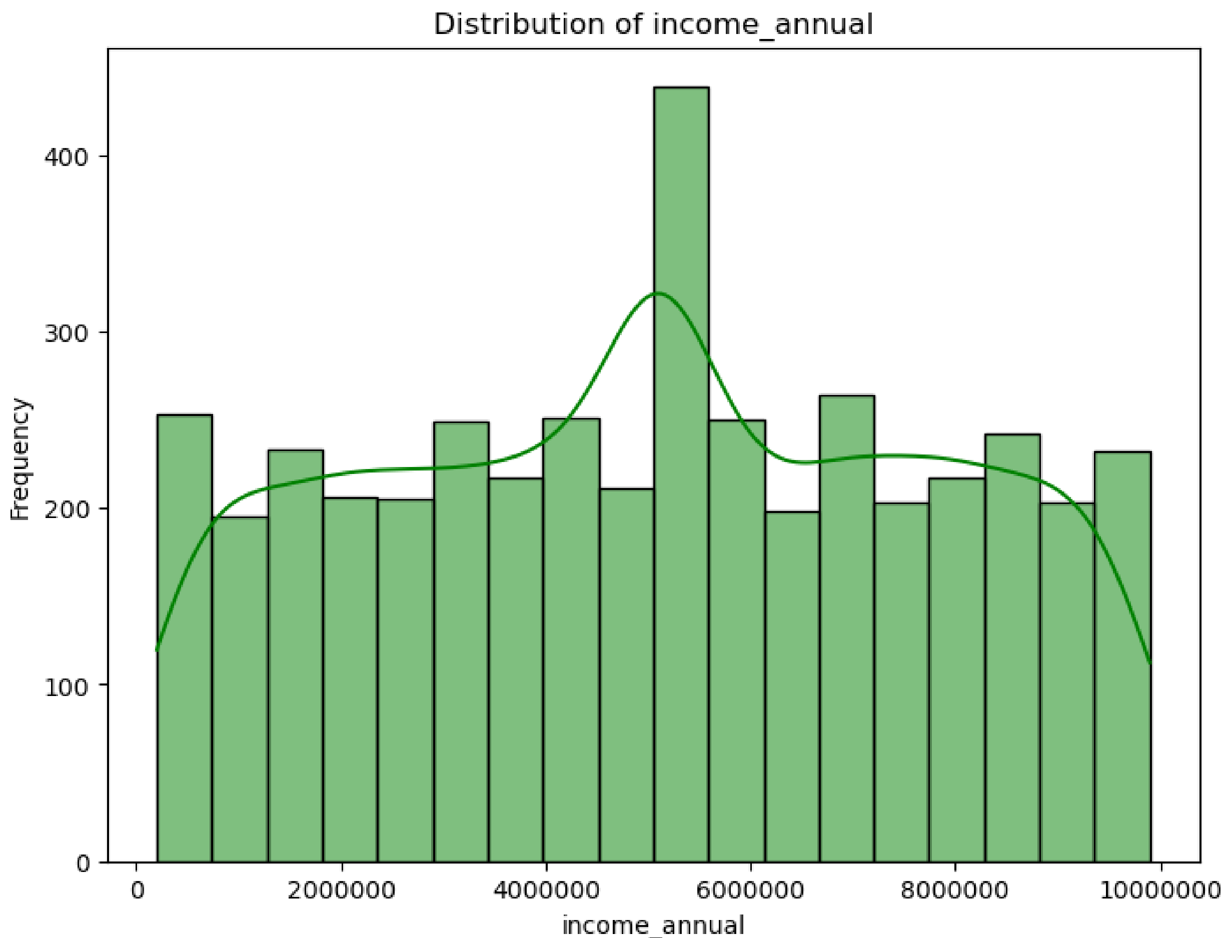
```
max      20.000000   900.000000              2.910000e+07

       commercial_assets_value  luxury_assets_value  bank_asset_value

count               4.268000e+03         4.268000e+03      3.927000e+03

mean                4.971556e+06         1.512149e+07      4.958365e+06

std                 4.388236e+06         9.099370e+06      3.262255e+06

min                 0.000000e+00         3.000000e+05      0.000000e+00

25%                 1.300000e+06         7.500000e+06      2.300000e+06

50%                 3.700000e+06         1.460000e+07      4.500000e+06

75%                 7.600000e+06         2.170000e+07      7.100000e+06

max                 1.940000e+07         3.920000e+07      1.470000e+07


# Summary of categorical data
categorical_descriptive_stats = data.describe(include=['O'])
categorical_descriptive_stats

        education self_employed loan_status
count        4268          4268        4268
unique          2             2           2
top      Graduate           Yes    Approved
freq         2143          2150        2655

# Grouping by education and self_employed to compare loan status
counts
education_loan_status = data.groupby(['education',
'loan_status']).size().unstack()
self_employed_loan_status = data.groupby(['self_employed',
'loan_status']).size().unstack()

education_loan_status, self_employed_loan_status

(loan_status     Approved   Rejected
 education
  Graduate           1338        805
  Not Graduate       1317        808,
 loan_status     Approved   Rejected
 self_employed
  No                 1317        801
  Yes                1338        812)

# Dropping unnecessary columns
data = data.drop(columns=['Unnamed: 0', 'id'])
```

```
# Handling missing values
imputer = SimpleImputer(strategy='median')
data[['income_annual', 'bank_asset_value']] =
imputer.fit_transform(data[['income_annual', 'bank_asset_value']])

# Encoding categorical variables
data['education'] = data['education'].map({' Graduate': 1, ' Not
Graduate': 0})
data['self_employed'] = data['self_employed'].map({' Yes': 1, ' No':
0})
data['loan_status'] = data['loan_status'].map({' Approved': 1, '
Rejected': 0})

# Filling Negative Values with mean
mean_non_negative = data[data['residential_assets_value'] >= 0]
['residential_assets_value'].mean()
data.loc[data['residential_assets_value'] < 0,
'residential_assets_value'] = mean_non_negative

data.iloc[:, :-1].describe()
```

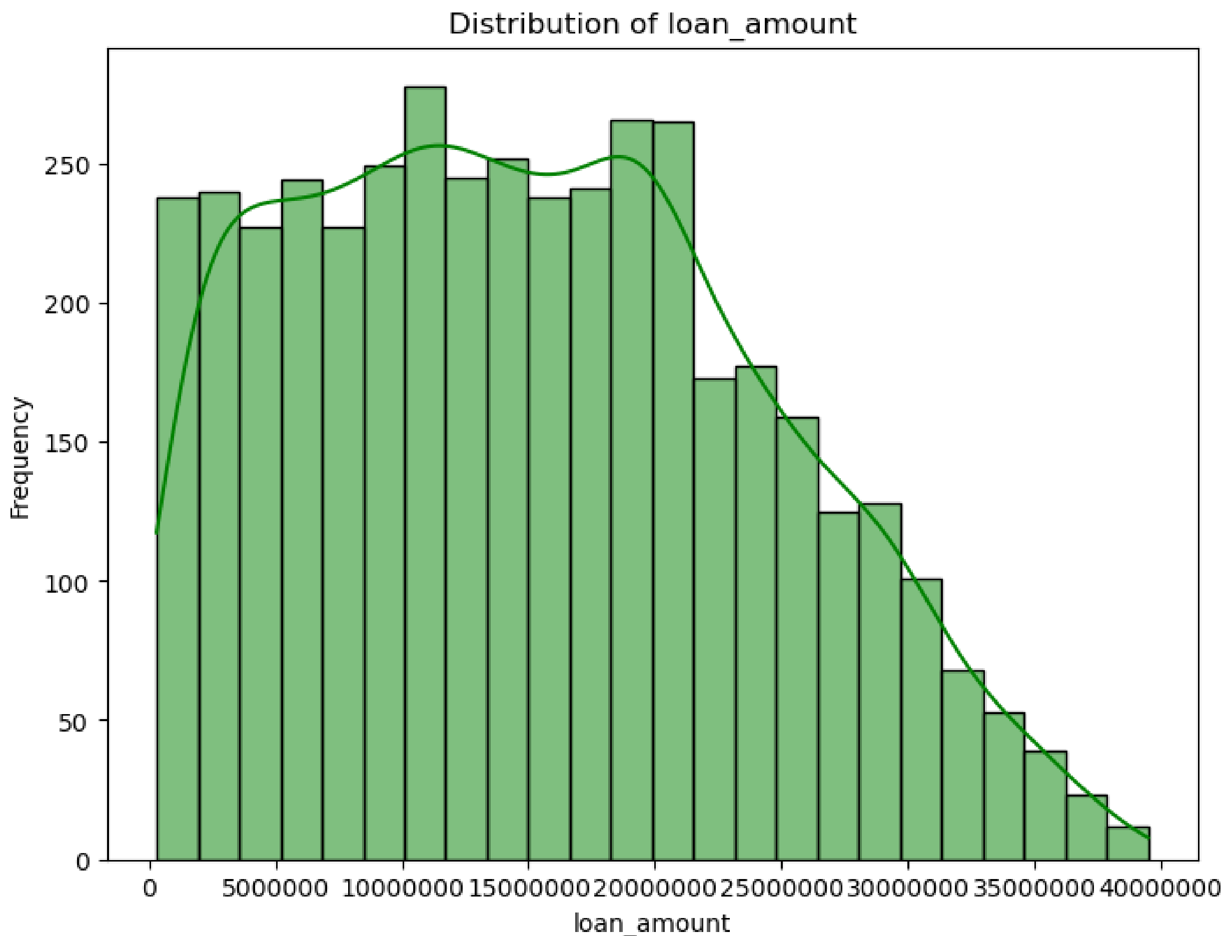
```
        dependents    education  self_employed  income_annual
loan_amount  \
count  4268.000000  4268.000000    4268.000000   4.268000e+03
4.268000e+03
mean      2.499063     0.502109       0.503749   5.051945e+06
1.513004e+07
std       1.695954     0.500054       0.500045   2.728357e+06
9.041673e+06
min       0.000000     0.000000       0.000000   2.000000e+05
3.000000e+05
25%       1.000000     0.000000       0.000000   2.800000e+06
7.700000e+06
50%       3.000000     1.000000       1.000000   5.100000e+06
1.450000e+07
75%       4.000000     1.000000       1.000000   7.300000e+06
2.150000e+07
max       5.000000     1.000000       1.000000   9.900000e+06
3.950000e+07

         loan_term  cibil_score  residential_assets_value  \
count  4268.000000  4268.000000              4.268000e+03
mean     10.900656   599.934396              7.520189e+06
std       5.709840   172.450571              6.473304e+06
min       2.000000   300.000000              0.000000e+00
25%       6.000000   453.000000              2.200000e+06
50%      10.000000   600.000000              5.800000e+06
75%      16.000000   748.000000              1.130000e+07
max      20.000000   900.000000              2.910000e+07
```

	commercial_assets_value	luxury_assets_value	bank_asset_value
count	4.268000e+03	4.268000e+03	4.268000e+03
mean	4.971556e+06	1.512149e+07	4.921743e+06
std	4.388236e+06	9.099370e+06	3.131656e+06
min	0.000000e+00	3.000000e+05	0.000000e+00
25%	1.300000e+06	7.500000e+06	2.500000e+06
50%	3.700000e+06	1.460000e+07	4.500000e+06
75%	7.600000e+06	2.170000e+07	6.800000e+06
max	1.940000e+07	3.920000e+07	1.470000e+07

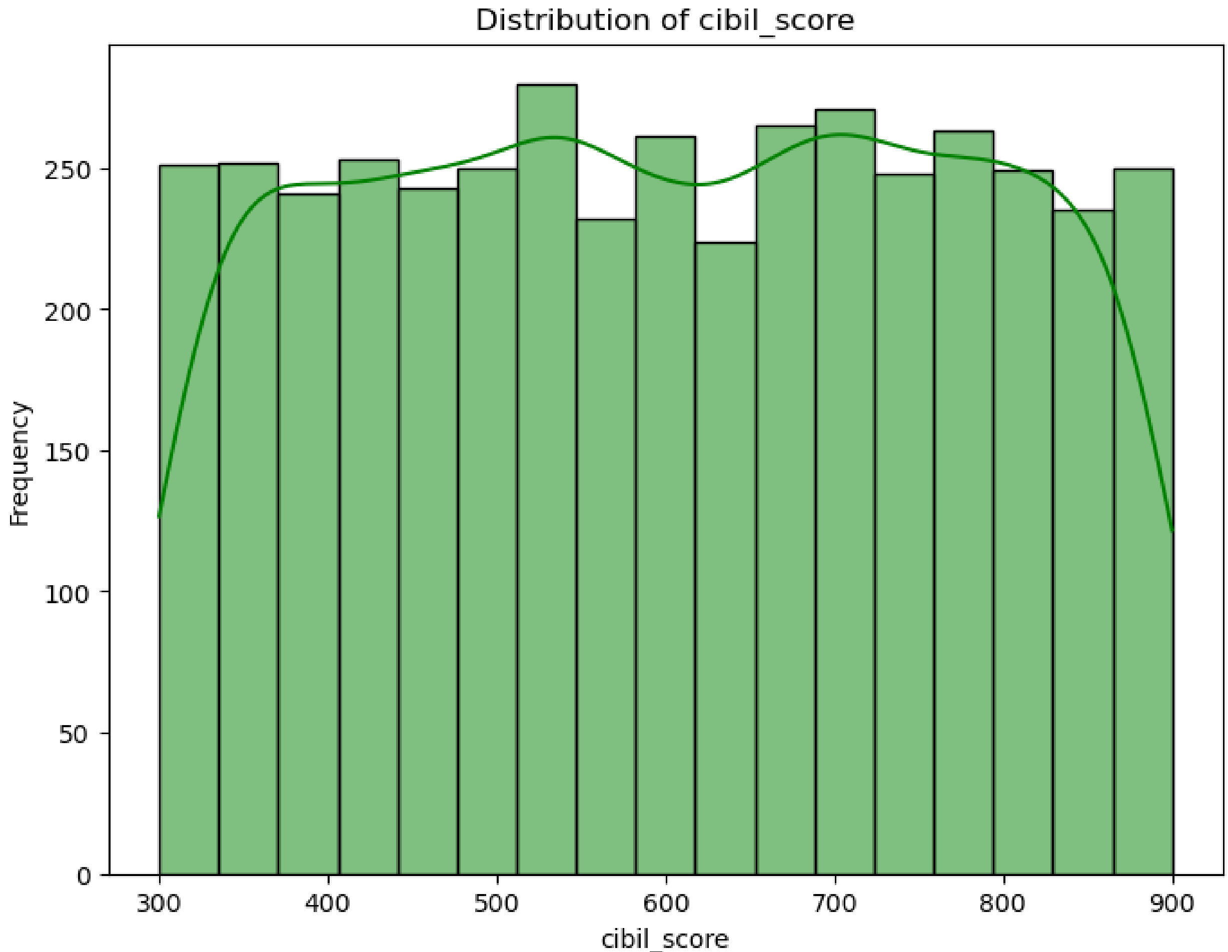
```
import seaborn as sns
import matplotlib.pyplot as plt

# Histograms
numerical_vars = ['income_annual', 'loan_amount', 'cibil_score']
for var in numerical_vars:
    plt.figure(figsize=(8, 6))
    ax = sns.histplot(data=data, x=var, kde=True, color='green')
    ax.ticklabel_format(style='plain', axis='x')  # Disable scientific
notation
    plt.title(f'Distribution of {var}')
    plt.xlabel(var)
    plt.ylabel('Frequency')
    plt.show()
```



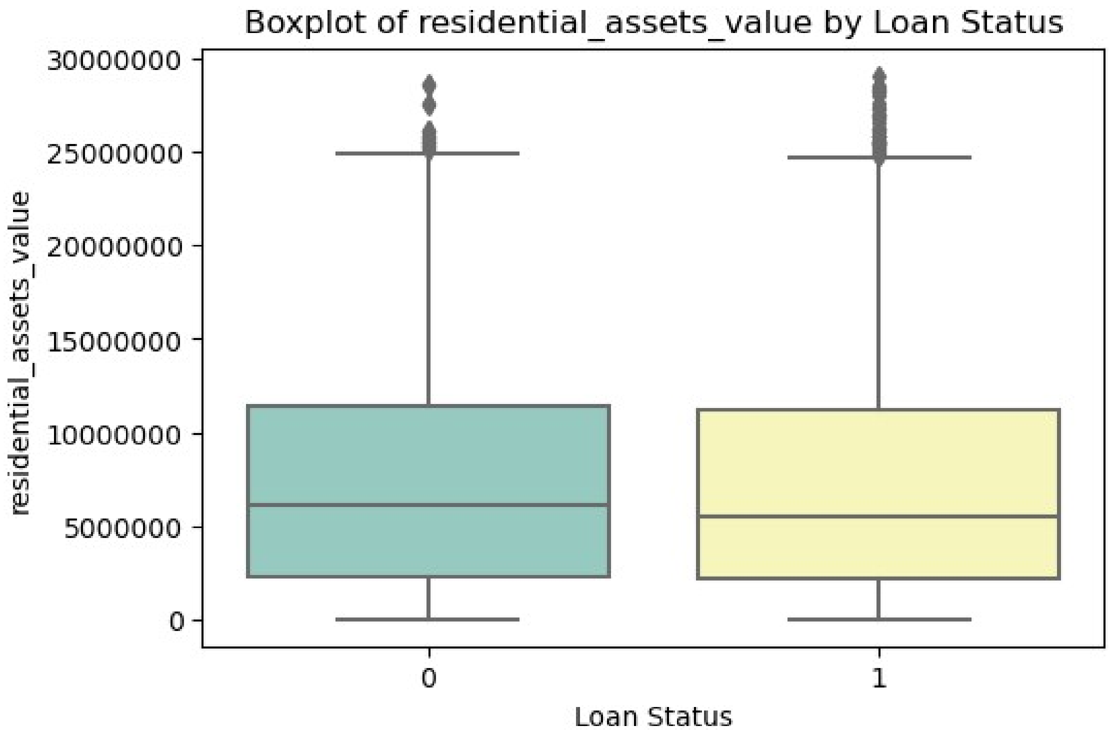
Distribution of income_annual
Frequency
400
300
200
100
0
0
2000000
4000000
6000000
8000000
10000000
income_annual

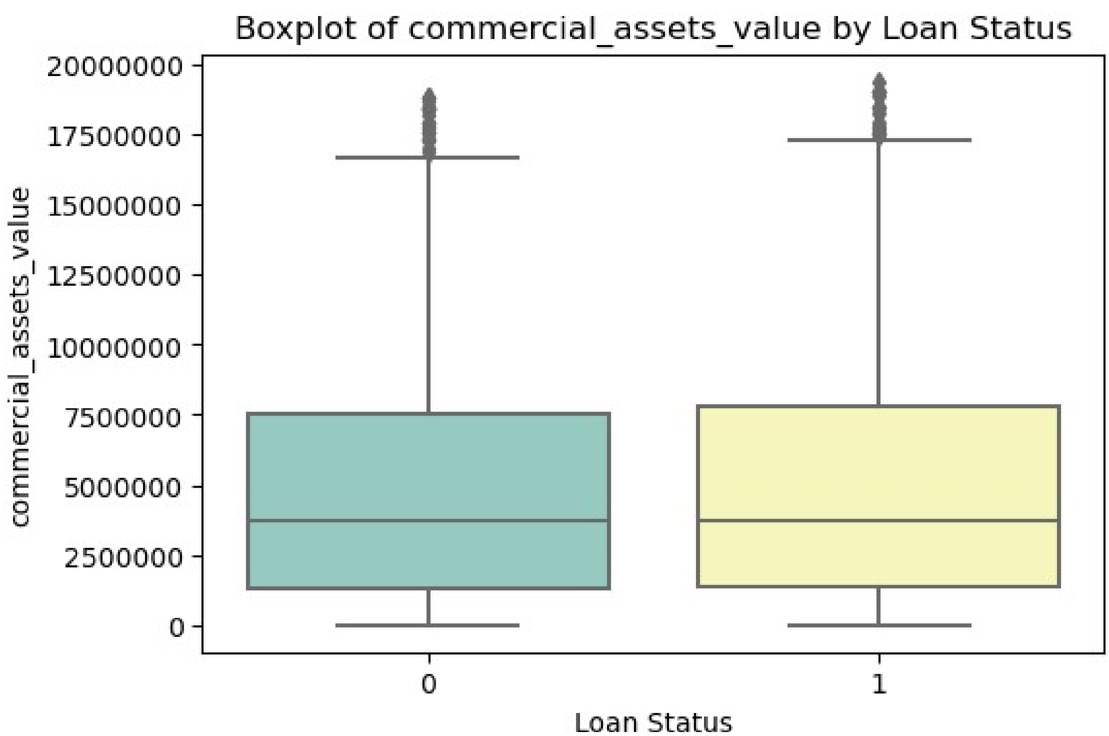


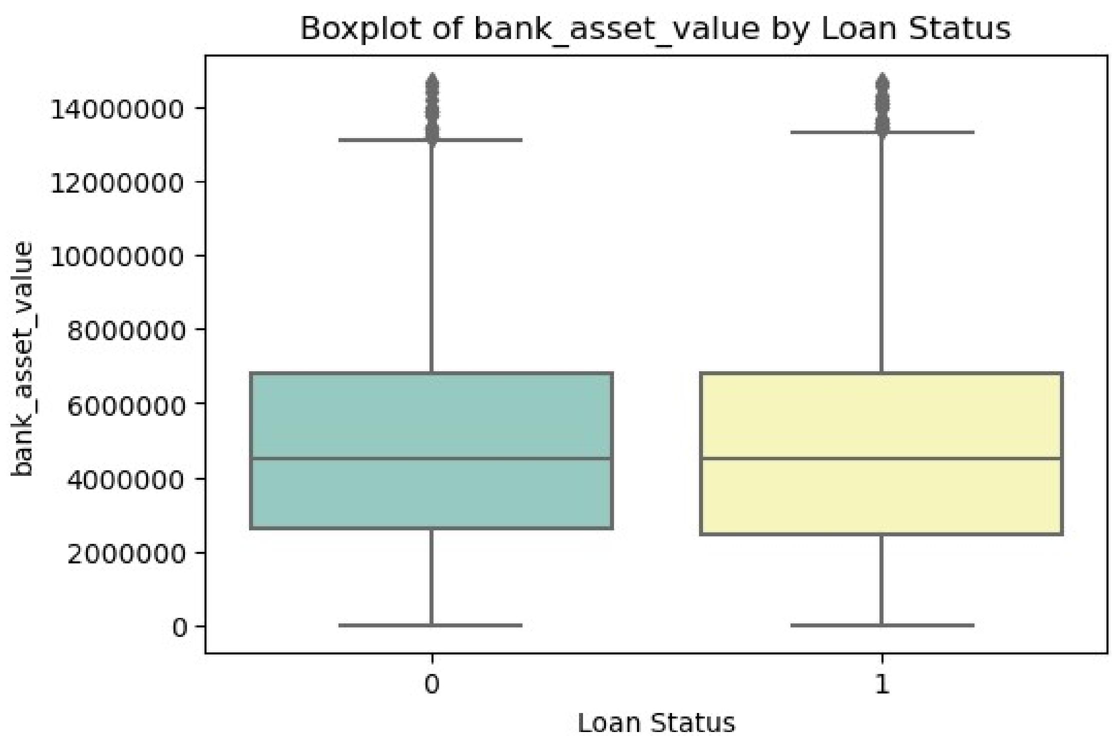
Distribution of loan_amount
Frequency
loan_amount
0
50
100
150
200
250
0
5000000
10000000
15000000
20000000
25000000
30000000
35000000
40000000




```
import seaborn as sns
import matplotlib.pyplot as plt

# Selecting different numerical variables for box plots
other_numerical_vars = ['residential_assets_value',
'commercial_assets_value', 'luxury_assets_value', 'bank_asset_value']

# Boxplots for the selected numerical variables
for var in other_numerical_vars:
    plt.figure(figsize=(6, 4))
    ax = sns.boxplot(x='loan_status', y=var, data=data,
palette='Set3')
    ax.ticklabel_format(style='plain', axis='y')
    plt.title(f'Boxplot of {var} by Loan Status')
    plt.xlabel('Loan Status')
    plt.ylabel(var)
    plt.show()
```

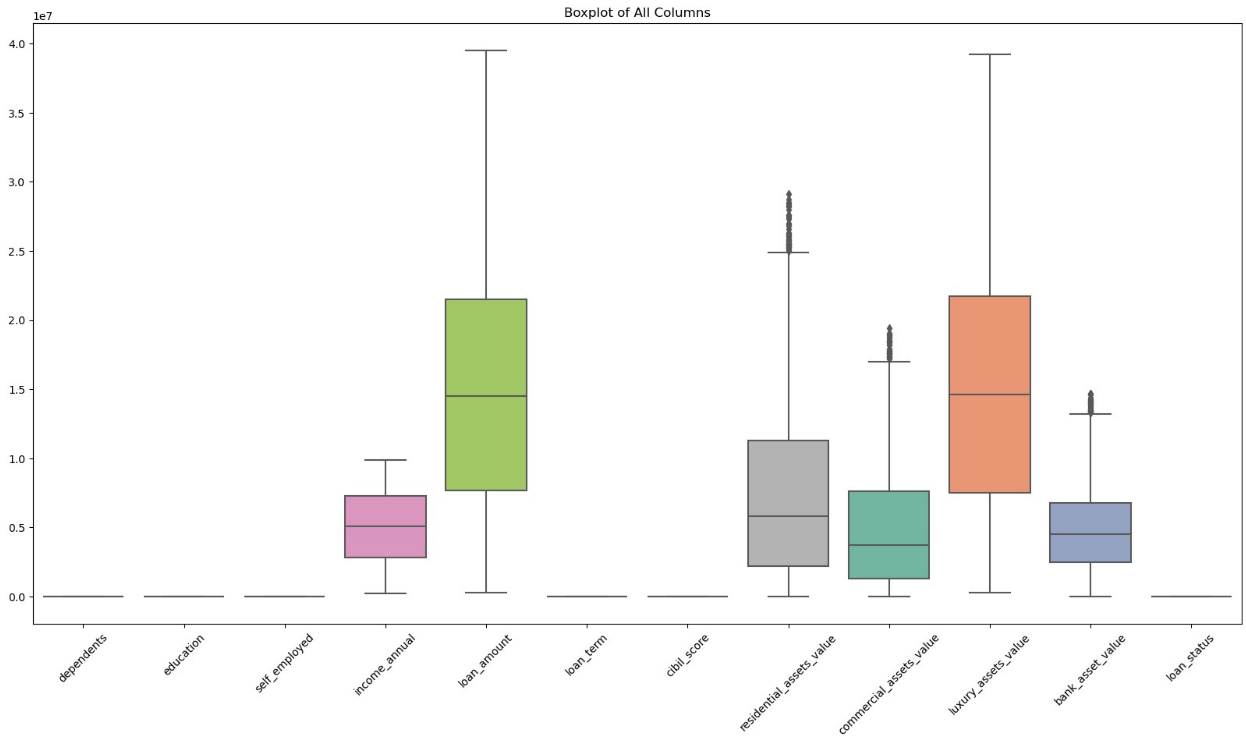

Boxplot of residential_assets_value by Loan Status
30000000
25000000
20000000
15000000
10000000
5000000
0
residential_assets_value
0
1
Loan Status


Boxplot of commercial_assets_value by Loan Status
20000000
17500000
15000000
12500000
10000000
7500000
5000000
2500000
0
commercial_assets_value
0
1
Loan Status




```
import seaborn as sns
import matplotlib.pyplot as plt

# Boxplots for all columns
```

```
plt.figure(figsize=(20, 10))
sns.boxplot(data=data, palette='Set2')
plt.title('Boxplot of All Columns')
plt.xticks(rotation=45)
plt.show()
```

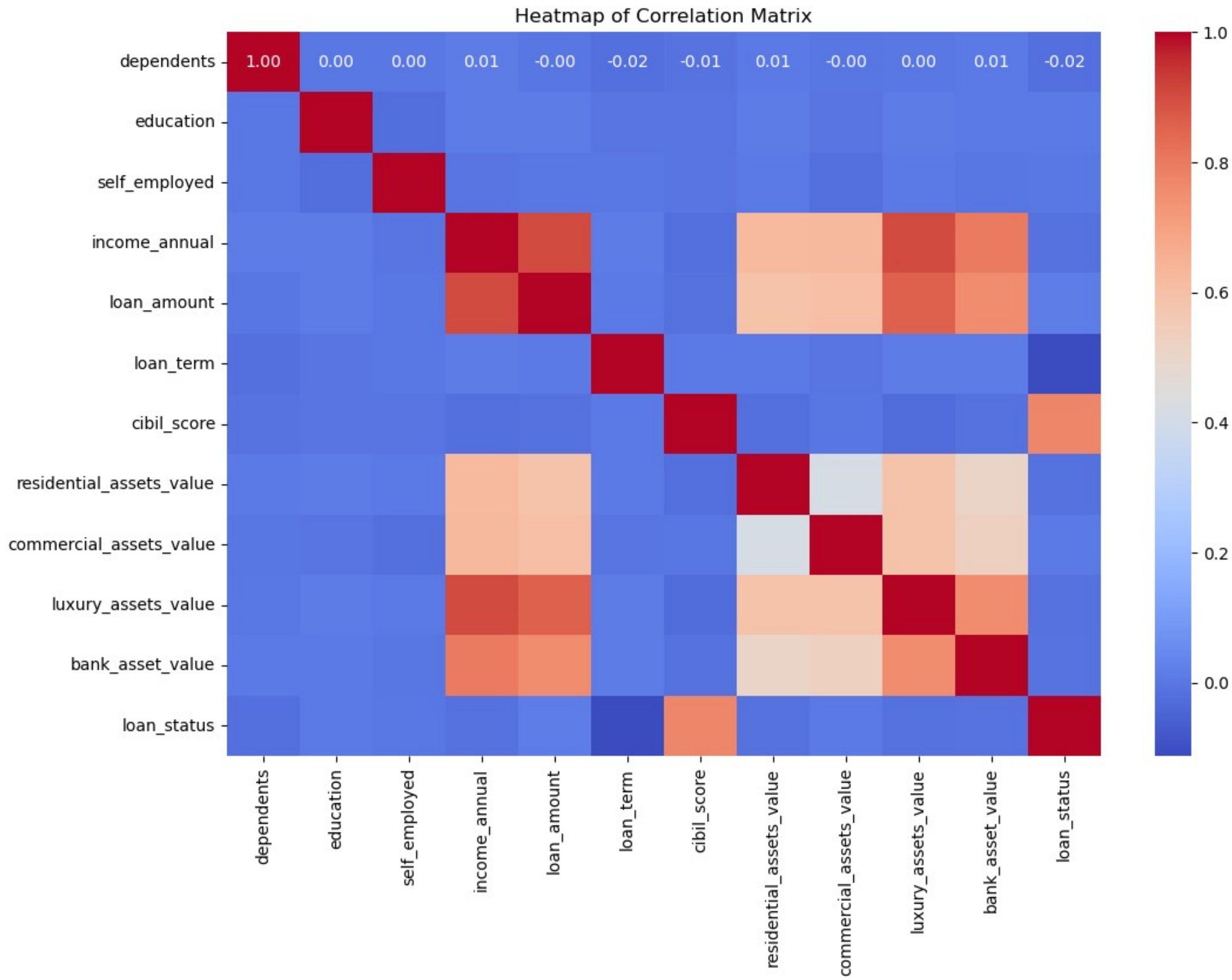



```
data.head()

   dependents  education  self_employed  income_annual  loan_amount  \
0           2          1              0      9600000.0     29900000
1           0          0              1      4100000.0     12200000
2           3          1              0      9100000.0     29700000
3           3          1              0      8200000.0     30700000
4           5          0              1      9800000.0     24200000

   loan_term  cibil_score  residential_assets_value
commercial_assets_value  \
0         12          778                 2400000.0
17600000
1          8          417                 2700000.0
2200000
2         20          506                 7100000.0
4500000
3          8          467                18200000.0
3300000
4         20          382                12400000.0
8200000
```

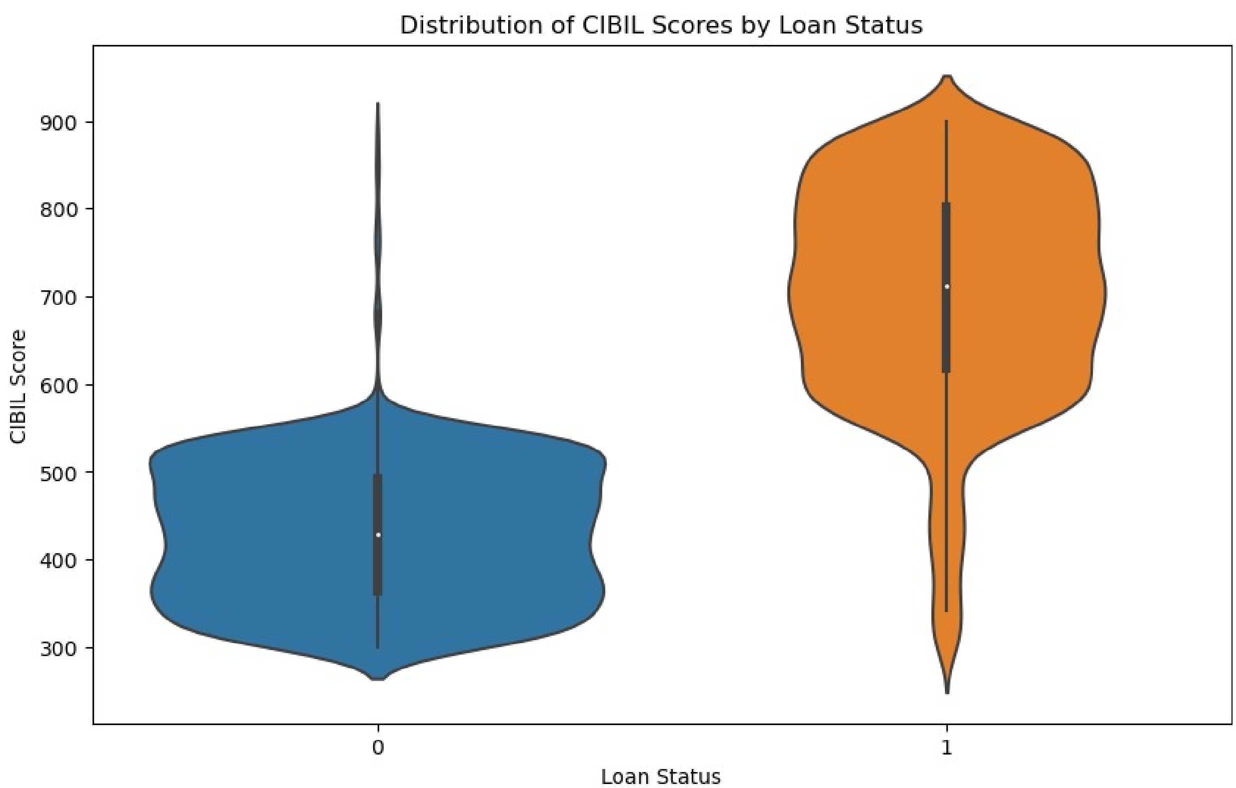
```
   luxury_assets_value  bank_asset_value  loan_status
0             22700000         4500000.0            1
1              8800000         3300000.0            0
2             33300000        12800000.0            0
3             23300000         7900000.0            0
4             29400000         5000000.0            0

# Calculate the correlation matrix for numerical columns
correlation_matrix = data.corr()
correlation_matrix

                          dependents  education  self_employed
income_annual  \
dependents                  1.000000   0.002904       0.000557
0.009312
education                   0.002904   1.000000      -0.022994
0.013018
self_employed               0.000557  -0.022994       1.000000       -
0.004497
income_annual               0.009312   0.013018      -0.004497
1.000000
loan_amount                -0.003033   0.010259       0.001831
0.901647
loan_term                  -0.020145  -0.008381       0.004070
0.012515
cibil_score                -0.009991  -0.004659      -0.004856       -
0.019911
residential_assets_value    0.008234   0.012234       0.007044
0.617785
commercial_assets_value    -0.001210  -0.007128      -0.017638
0.625112
luxury_assets_value         0.003287   0.011952       0.004950
0.902909
bank_asset_value            0.008374   0.008546      -0.001429
0.796866
loan_status                -0.017956   0.004737       0.000529       -
0.014084

                          loan_amount  loan_term  cibil_score  \
dependents                  -0.003033  -0.020145    -0.009991
education                    0.010259  -0.008381    -0.004659
self_employed                0.001831   0.004070    -0.004856
income_annual                0.901647   0.012515    -0.019911
loan_amount                  1.000000   0.008499    -0.017055
loan_term                    0.008499   1.000000     0.007811
cibil_score                 -0.017055   0.007811     1.000000
residential_assets_value     0.591217   0.007764    -0.018359
commercial_assets_value      0.602955  -0.005422    -0.003785
luxury_assets_value          0.860838   0.012581    -0.028656
```

```
bank_asset_value             0.754248   0.012650    -0.015995
loan_status                  0.015861  -0.113015     0.770566

                          residential_assets_value
commercial_assets_value  \
dependents                                0.008234                 -
0.001210
education                                 0.012234                 -
0.007128
self_employed                             0.007044                 -
0.017638
income_annual                             0.617785
0.625112
loan_amount                               0.591217
0.602955
loan_term                                 0.007764                 -
0.005422
cibil_score                              -0.018359                 -
0.003785
residential_assets_value                  1.000000
0.413127
commercial_assets_value                   0.413127
1.000000
luxury_assets_value                       0.587511
0.590825
bank_asset_value                          0.505198
0.527509
loan_status                              -0.015535
0.007965

                          luxury_assets_value  bank_asset_value
loan_status
dependents                           0.003287          0.008374    -
0.017956
education                            0.011952          0.008546
0.004737
self_employed                        0.004950         -0.001429
0.000529
income_annual                        0.902909          0.796866    -
0.014084
loan_amount                          0.860838          0.754248
0.015861
loan_term                            0.012581          0.012650    -
0.113015
cibil_score                         -0.028656         -0.015995
0.770566
residential_assets_value             0.587511          0.505198    -
0.015535
commercial_assets_value              0.590825          0.527509
```

```
0.007965
luxury_assets_value                          1.000000            0.756503    -
0.015888
bank_asset_value                             0.756503            1.000000    -
0.012366
loan_status                                 -0.015888           -0.012366
1.000000

# Calculating the correlation matrix
correlation_matrix = data.corr()

# Plotting the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f",
cmap='coolwarm', cbar=True)
plt.title('Heatmap of Correlation Matrix')
plt.show()
```



```
# Creating a violin plot for CIBIL scores by Loan Status
plt.figure(figsize=(10, 6))
sns.violinplot(x='loan_status', y='cibil_score', data=data)
plt.title('Distribution of CIBIL Scores by Loan Status')
plt.xlabel('Loan Status')
plt.ylabel('CIBIL Score')
plt.show()
```




```
# Splitting data into features and target variable
X = data.drop(['loan_status'], axis=1)
Y = data['loan_status']

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, Y,
test_size=0.2, random_state=42)
```

SVM Model

```
from sklearn.preprocessing import StandardScaler

# Create a scaler object
scaler = StandardScaler()

# Fit on training data and transform both training and testing sets
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

from sklearn.svm import SVC

# Initializing and training the SVM model
svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train_scaled, y_train)

SVC(kernel='linear', random_state=42)

from sklearn.metrics import accuracy_score, classification_report

# Predict the labels for the test set
y_pred = svm_model.predict(X_test_scaled)

# Calculate the accuracy and classification report
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print("Accuracy:", accuracy)
print("Classification Report:\n", report)

Accuracy: 0.9203747072599532
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.89      0.89       303
           1       0.94      0.93      0.94       551

    accuracy                           0.92       854
   macro avg       0.91      0.91      0.91       854
weighted avg       0.92      0.92      0.92       854
```

Hyperparameter Tuning

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

# Define the model to be tuned
svm_classifier = SVC(random_state=42)

# Define the hyperparameter grid
param_grid = {
    'C': [0.1, 1, 10, 100],  # Regularization parameter
    'kernel': ['linear', 'rbf', 'poly'],  # Type of SVM kernel to be
used
    'gamma': ['scale', 'auto'],  # Kernel coefficient for 'rbf',
'poly'
    'degree': [2, 3, 4]  # Degree of the polynomial kernel function
```

```
(‘poly’).
}

# Setup the grid search with cross-validation
svm_grid_search = GridSearchCV(estimator=svm_classifier,
param_grid=param_grid, cv=5,scoring='accuracy', verbose=1)

# Fit the grid search to the data
svm_grid_search.fit(X_train_scaled, y_train)

Fitting 5 folds for each of 72 candidates, totalling 360 fits

GridSearchCV(cv=5, estimator=SVC(random_state=42),
             param_grid={'C': [0.1, 1, 10, 100], 'degree': [2, 3, 4],
                         'gamma': ['scale', 'auto'],
                         'kernel': ['linear', 'rbf', 'poly']},
             scoring='accuracy', verbose=1)

# Print the best parameters and best score
print("Best parameters:", grid_search_svm.best_params_)
print("Best cross-validation score:
{:.2f}".format(svm_grid_search.best_score_))

Best parameters: {'C': 10, 'degree': 2, 'gamma': 'scale', 'kernel':
'rbf'}
Best cross-validation score: 0.94

# Use the best estimator to make predictions on test data
y_pred_svm = svm_grid_search.best_estimator_.predict(X_test_scaled)

# Evaluate the best model on the test set
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print("Test set accuracy: {:.2f}".format(accuracy_svm))

Test set accuracy: 0.94

# Use the best estimator to make predictions on train data
y_pred_svm_train =
grid_search_svm.best_estimator_.predict(X_train_scaled)

# Evaluate the best model on the train set
accuracy_svm_train = accuracy_score(y_train, y_pred_svm_train)
print("Train set accuracy: {:.2f}".format(accuracy_svm_train))

Train set accuracy: 0.98

from sklearn.metrics import precision_score, recall_score, f1_score


# Calculate precision, recall, and F1 score
precision_svm = precision_score(y_test, y_pred_svm)
recall_svm = recall_score(y_test, y_pred_svm)
```

```
f1_svm = f1_score(y_test, y_pred_svm)

print("Precision:", precision_svm)
print("Recall:", recall_svm)
print("F1 Score:", f1_svm)
```

```
Precision: 0.9579524680073126
Recall: 0.9509981851179673
F1 Score: 0.9544626593806921
```

Multilayer Perceptron

```
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, classification_report

# Initialize the MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(100, 50),  # This is the size 
of the hidden layer(s)
                    activation='relu',          # Activation function 
for the hidden layer
                    solver='adam',              # The solver for weight 
optimization
                    max_iter=300,               # Maximum number of 
iterations
                    random_state=42)

# Fit the model to the scaled training data
mlp.fit(X_train_scaled, y_train)
```

```
MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=300, 
random_state=42)
```

```
# Make predictions with the model
y_pred = mlp.predict(X_test_scaled)

# Calculate the accuracy and print classification report
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print("Accuracy:", accuracy)
print("Classification Report:\n", report)
```

```
Accuracy: 0.9601873536299765
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.95      0.94       303
           1       0.97      0.97      0.97       551

    accuracy                           0.96       854
   macro avg       0.96      0.96      0.96       854
```

```
weighted avg       0.96      0.96      0.96       854
```

Hyperparameter Tuning

```
from sklearn.model_selection import GridSearchCV

# Define the MLP model
mlp = MLPClassifier(max_iter=1000, random_state=42)  # Increase
max_iter for convergence

# Define the parameter grid to search
parameter_space = {
    'hidden_layer_sizes': [(50,), (100,), (50, 50), (100, 100)],
    'activation': ['tanh', 'relu'],
    'solver': ['adam'],  # 'sgd' removed as it tends to perform worse
    'alpha': [0.0001, 0.05],
    'learning_rate_init': [0.001, 0.01],  # Added learning_rate_init
for learning rate adjustment
}

# Set up GridSearchCV
mlp_grid_search = GridSearchCV(mlp, parameter_space, n_jobs=-1,
cv=3,scoring='accuracy', verbose=2)

# Fit GridSearchCV
mlp_grid_search.fit(X_train_scaled, y_train)
```

```
Fitting 3 folds for each of 32 candidates, totalling 96 fits
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/neural_network/
_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic
Optimizer: Maximum iterations (1000) reached and the optimization
hasn't converged yet.
  warnings.warn(
/opt/anaconda3/lib/python3.11/site-packages/sklearn/neural_network/
_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic
Optimizer: Maximum iterations (1000) reached and the optimization
hasn't converged yet.
  warnings.warn(
/opt/anaconda3/lib/python3.11/site-packages/sklearn/neural_network/
_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic
Optimizer: Maximum iterations (1000) reached and the optimization
hasn't converged yet.
  warnings.warn(
```

```
GridSearchCV(cv=3, estimator=MLPClassifier(max_iter=1000,
random_state=42),
             n_jobs=-1,
             param_grid={'activation': ['tanh', 'relu'],
                         'alpha': [0.0001, 0.05],
```

```
                         'hidden_layer_sizes': [(50,), (100,), (50,
50),
                                                (100, 100)],
                         'learning_rate_init': [0.001, 0.01],
                         'solver': ['adam']},
             scoring='accuracy', verbose=2)
```

```
# Best parameter set
print('Best parameters found:\n', mlp_grid_search.best_params_)
```

```
Best parameters found:
 {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (100,
100), 'learning_rate_init': 0.001, 'solver': 'adam'}
```

```
means = mlp_grid_search.cv_results_['mean_test_score']
stds = mlp_grid_search.cv_results_['std_test_score']
for mean, std, params in zip(means, stds,
mlp_grid_search.cv_results_['params']):
    print("%0.3f (+/-%0.03f) for %r" % (mean, std * 2, params))
```

```
0.962 (+/-0.016) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.955 (+/-0.010) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.958 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.958 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.960 (+/-0.015) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.964 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.965 (+/-0.007) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.001,
'solver': 'adam'}
0.958 (+/-0.033) for {'activation': 'tanh', 'alpha': 0.0001,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.01,
'solver': 'adam'}
0.963 (+/-0.015) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.962 (+/-0.021) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.01, 'solver':
'adam'}
```

```
0.964 (+/-0.017) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.961 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.962 (+/-0.013) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.965 (+/-0.015) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.968 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.001,
'solver': 'adam'}
0.961 (+/-0.020) for {'activation': 'tanh', 'alpha': 0.05,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.01,
'solver': 'adam'}
0.955 (+/-0.011) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.951 (+/-0.006) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.953 (+/-0.021) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.951 (+/-0.012) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.953 (+/-0.010) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.959 (+/-0.017) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.953 (+/-0.011) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.001,
'solver': 'adam'}
0.951 (+/-0.017) for {'activation': 'relu', 'alpha': 0.0001,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.01,
'solver': 'adam'}
0.960 (+/-0.016) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.958 (+/-0.018) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (50,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.955 (+/-0.022) for {'activation': 'relu', 'alpha': 0.05,
```

```
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.957 (+/-0.013) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (100,), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.957 (+/-0.015) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.001, 'solver':
'adam'}
0.960 (+/-0.010) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (50, 50), 'learning_rate_init': 0.01, 'solver':
'adam'}
0.959 (+/-0.013) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.001,
'solver': 'adam'}
0.957 (+/-0.018) for {'activation': 'relu', 'alpha': 0.05,
'hidden_layer_sizes': (100, 100), 'learning_rate_init': 0.01,
'solver': 'adam'}
```

```
# Predict on the test set using the best model
y_pred_mlp = mlp_grid_search.best_estimator_.predict(X_test_scaled)

accuracy_mlp = accuracy_score(y_test, y_pred_mlp)
accuracy_mlp
```

```
0.9660421545667447
```

```
# Print classification report
print(classification_report(y_test, y_pred_mlp))
```

```
              precision    recall  f1-score   support

           0       0.97      0.94      0.95       303
           1       0.97      0.98      0.97       551

    accuracy                           0.97       854
   macro avg       0.97      0.96      0.96       854
weighted avg       0.97      0.97      0.97       854
```

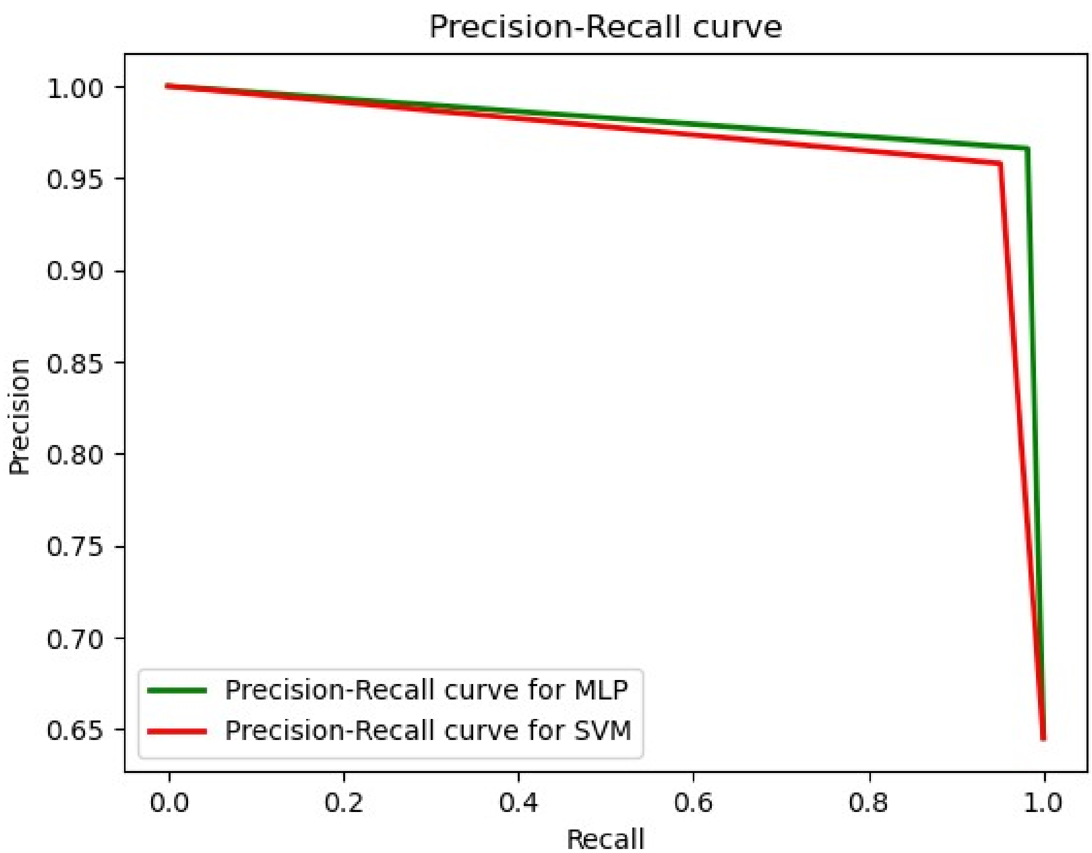
```
from sklearn.metrics import precision_score, recall_score, f1_score


# Calculate precision, recall, and F1 score
precision_mlp = precision_score(y_test, y_pred_mlp)
recall_mlp = recall_score(y_test, y_pred_mlp)
f1_mlp = f1_score(y_test, y_pred_mlp)

print("Precision:", precision_mlp)
print("Recall:", recall_mlp)
print("F1 Score:", f1_mlp)
```

```
Precision: 0.9660714285714286
Recall: 0.9818511796733213
F1 Score: 0.9738973897389739
```

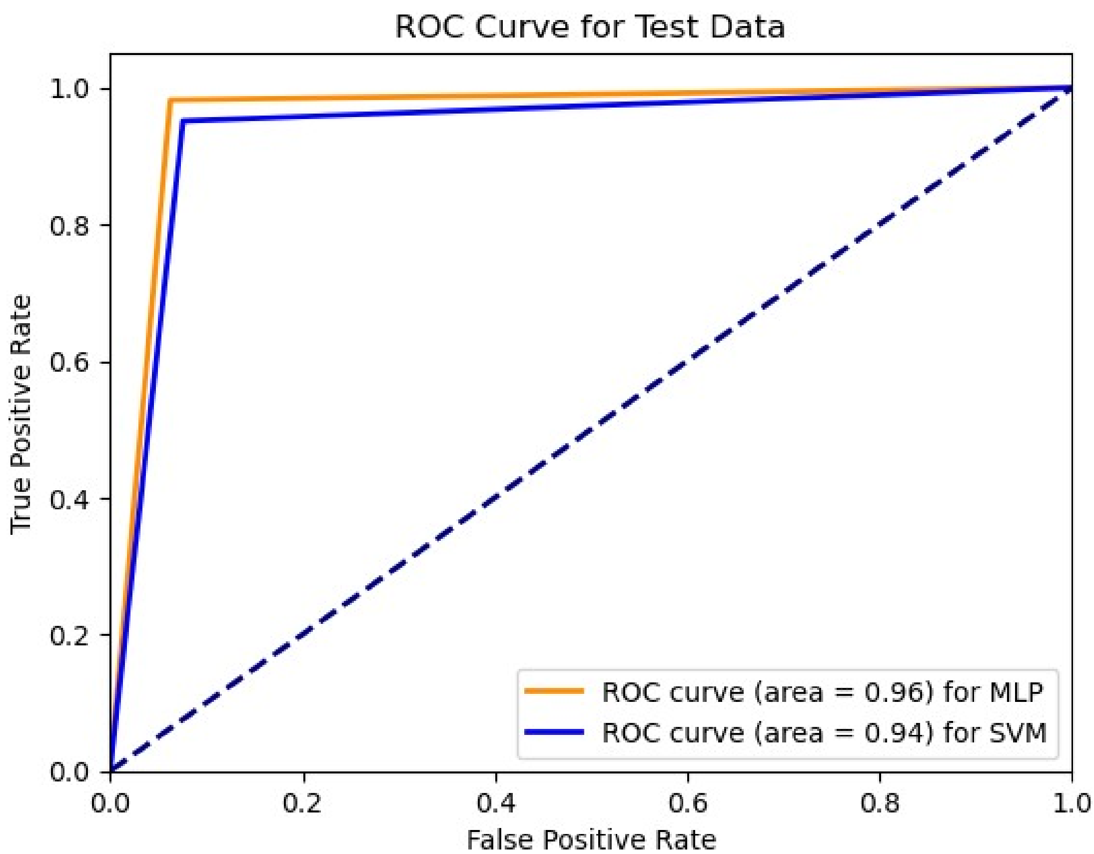
```python
# Predict on the train set using the best model
y_pred_mlp_train =
mlp_grid_search.best_estimator_.predict(X_train_scaled)

accuracy_mlp_train = accuracy_score(y_train, y_pred_mlp_train)
accuracy_mlp_train
```

```
0.9824253075571178
```

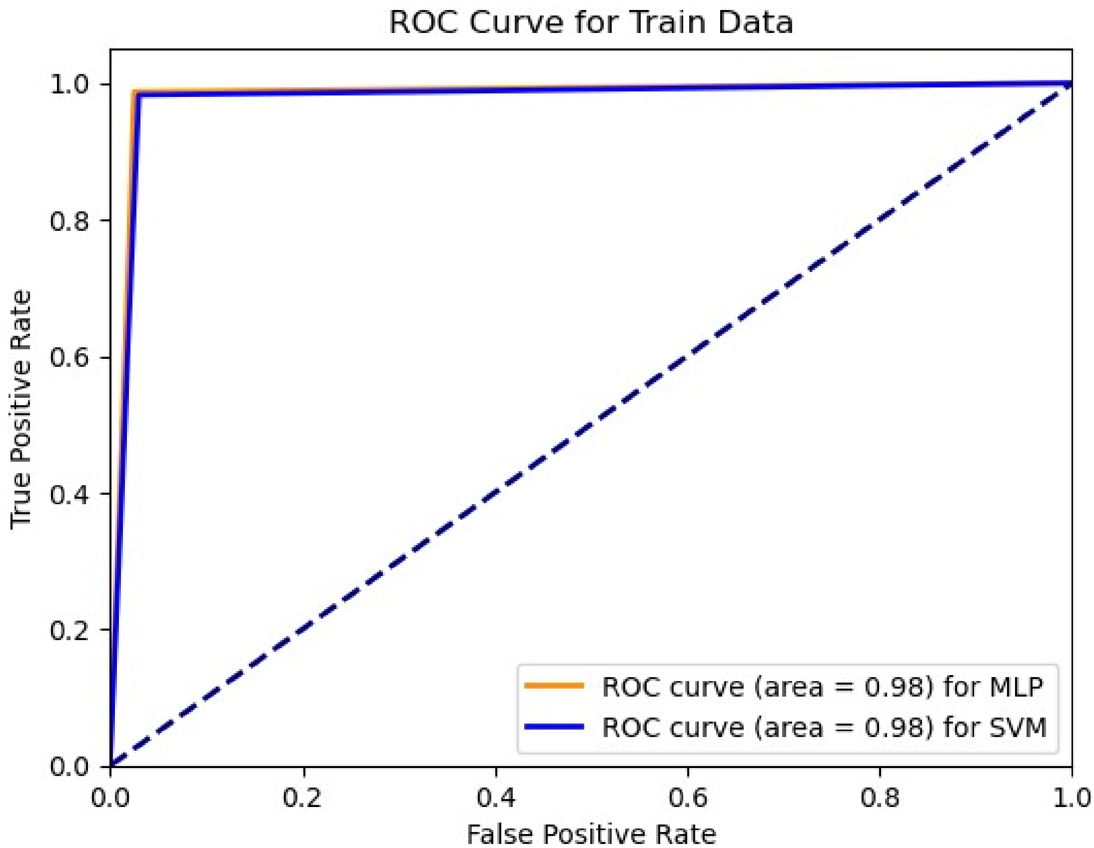
```python
from sklearn.metrics import precision_recall_curve

precision_mlp, recall_mlp, _ = precision_recall_curve(y_test,
y_pred_mlp)
precision_svm, recall_svm, _ = precision_recall_curve(y_test,
y_pred_svm)

plt.figure()
plt.plot(recall_mlp, precision_mlp, color='green', lw=2,
label='Precision-Recall curve for MLP')
plt.plot(recall_svm, precision_svm, color='red', lw=2,
label='Precision-Recall curve for SVM')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall curve')
plt.legend(loc="lower left")
plt.show()
```



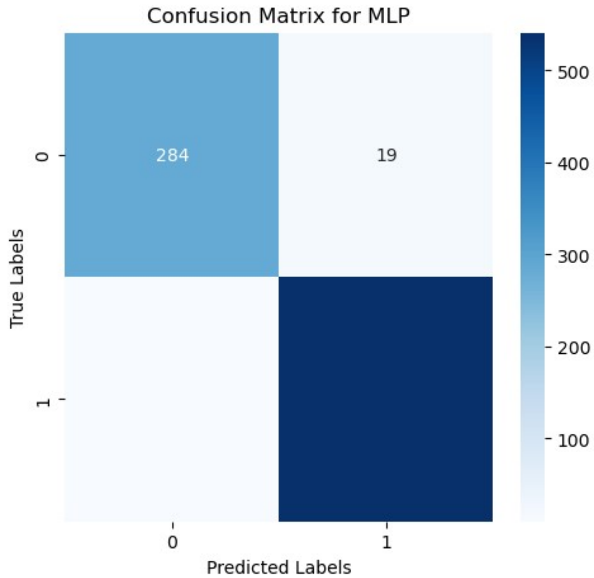

```
from sklearn.metrics import roc_curve, auc

fpr_mlp, tpr_mlp, _ = roc_curve(y_test, y_pred_mlp)
roc_auc_mlp = auc(fpr_mlp, tpr_mlp)

fpr_svm, tpr_svm, _ = roc_curve(y_test, y_pred_svm)
roc_auc_svm = auc(fpr_svm, tpr_svm)

plt.figure()
plt.plot(fpr_mlp, tpr_mlp, color='darkorange', lw=2, label='ROC curve
(area = %0.2f) for MLP' % roc_auc_mlp)
plt.plot(fpr_svm, tpr_svm, color='blue', lw=2, label='ROC curve (area
= %0.2f) for SVM' % roc_auc_svm)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Test Data')
plt.legend(loc="lower right")
plt.show()
```

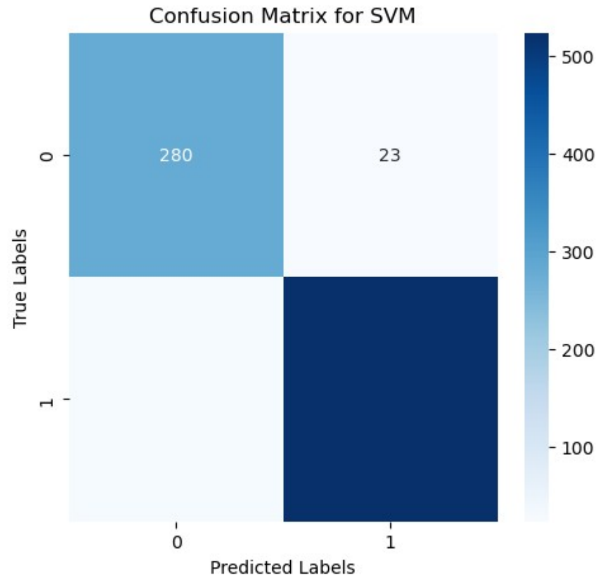



```
from sklearn.metrics import roc_curve, auc

fpr_mlp, tpr_mlp, _ = roc_curve(y_train, y_pred_mlp_train)
roc_auc_mlp = auc(fpr_mlp, tpr_mlp)

fpr_svm, tpr_svm, _ = roc_curve(y_train, y_pred_svm_train)
roc_auc_svm = auc(fpr_svm, tpr_svm)

plt.figure()
plt.plot(fpr_mlp, tpr_mlp, color='darkorange', lw=2, label='ROC curve
(area = %0.2f) for MLP' % roc_auc_mlp)
plt.plot(fpr_svm, tpr_svm, color='blue', lw=2, label='ROC curve (area
= %0.2f) for SVM' % roc_auc_svm)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Train Data')
plt.legend(loc="lower right")
plt.show()
```




```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

cm_mlp = confusion_matrix(y_test, y_pred_mlp)
cm_svm = confusion_matrix(y_test, y_pred_svm)

fig, ax = plt.subplots(1, 2, figsize=(12, 5))
sns.heatmap(cm_mlp, annot=True, fmt='d', cmap='Blues', ax=ax[0])
ax[0].set_title('Confusion Matrix for MLP')
ax[0].set_xlabel('Predicted Labels')
ax[0].set_ylabel('True Labels')

sns.heatmap(cm_svm, annot=True, fmt='d', cmap='Blues', ax=ax[1])
ax[1].set_title('Confusion Matrix for SVM')
ax[1].set_xlabel('Predicted Labels')
ax[1].set_ylabel('True Labels')
plt.show()
```






```
# We will create a DataFrame with test features and labels
test_data = pd.DataFrame(X_test_scaled)
test_data.reset_index(drop=True, inplace=True)
y_test.reset_index(drop=True, inplace=True)
test_data['True_Label'] = y_test  # Add the true labels as a new
column in the DataFrame

# Save the DataFrame to a CSV file
test_data.to_csv('test_data.csv', index=False)  # Set index=False not
to save the index

from joblib import dump

# Save the models to a file
dump(mlp_grid_search, 'mlp_grid_search.joblib')
dump(svm_grid_search, 'svm_grid_search.joblib')

['svm_grid_search.joblib']
```