Data Analysis and Credit Risk Modelling - **Loan Classification**

PROBLEM STATEMENT:

Understand and apply machine learning techniques to classify loan applicants based on their likelihood of loan repayment.

import necessary libararies

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import xgboost as xgb
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from scipy.stats import zscore
import warnings
warnings.filterwarnings("ignore")
import streamlit as st
```

Step 1: load the dataset

```
data = pd.read_csv('/loan_detection.csv')
```

Step 2: Initial Inspection

```
print("Data Head:")
print(data.head())
```

```
Data Head:
   age  campaign  pdays  previous  no_previous_contact  not_working  \
0   56         1    999         0                    1            0
1   57         1    999         0                    1            0
2   37         1    999         0                    1            0
3   40         1    999         0                    1            0
4   56         1    999         0                    1            0

   job_admin.  job_blue-collar  job_entrepreneur  job_housemaid  ...  \
0           0                0                 0              1  ...
1           0                0                 0              0  ...
2           0                0                 0              0  ...
3           1                0                 0              0  ...
4           0                0                 0              0  ...

   month_sep  day_of_week_fri  day_of_week_mon  day_of_week_thu  \
0          0                0                1                0
1          0                0                1                0
2          0                0                1                0
3          0                0                1                0
4          0                0                1                0

   day_of_week_tue  day_of_week_wed  poutcome_failure  poutcome_nonexistent  \
0                0                0                 0                     1
1                0                0                 0                     1
2                0                0                 0                     1
3                0                0                 0                     1
4                0                0                 0                     1

   poutcome_success  Loan_Status_label
0                 0                  0
1                 0                  0
2                 0                  0
3                 0                  0
4                 0                  0

[5 rows x 60 columns]
```

```
data.shape
```

```
(41188, 60)
```

```
print("\nData Info:")
print(data.info())
```

```
Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 60 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   age                            41188 non-null  int64
 1   campaign                       41188 non-null  int64
 2   pdays                          41188 non-null  int64
 3   previous                       41188 non-null  int64
 4   no_previous_contact            41188 non-null  int64
 5   not_working                    41188 non-null  int64
 6   job_admin.                     41188 non-null  int64
 7   job_blue-collar                41188 non-null  int64
 8   job_entrepreneur               41188 non-null  int64
 9   job_housemaid                  41188 non-null  int64
 10  job_management                 41188 non-null  int64
 11  job_retired                    41188 non-null  int64
 12  job_self-employed              41188 non-null  int64
 13  job_services                   41188 non-null  int64
 14  job_student                    41188 non-null  int64
 15  job_technician                 41188 non-null  int64
 16  job_unemployed                 41188 non-null  int64
 17  job_unknown                    41188 non-null  int64
 18  marital_divorced               41188 non-null  int64
 19  marital_married                41188 non-null  int64
 20  marital_single                 41188 non-null  int64
 21  marital_unknown                41188 non-null  int64
 22  education_basic.4y             41188 non-null  int64
 23  education_basic.6y             41188 non-null  int64
 24  education_basic.9y             41188 non-null  int64
 25  education_high.school          41188 non-null  int64
 26  education_illiterate           41188 non-null  int64
 27  education_professional.course  41188 non-null  int64
 28  education_university.degree    41188 non-null  int64
 29  education_unknown              41188 non-null  int64
 30  default_no                     41188 non-null  int64
 31  default_unknown                41188 non-null  int64
 32  default_yes                    41188 non-null  int64
 33  housing_no                     41188 non-null  int64
 34  housing_unknown                41188 non-null  int64
 35  housing_yes                    41188 non-null  int64
 36  loan_no                        41188 non-null  int64
 37  loan_unknown                   41188 non-null  int64
 38  loan_yes                       41188 non-null  int64
 39  contact_cellular               41188 non-null  int64
 40  contact_telephone              41188 non-null  int64
 41  month_apr                      41188 non-null  int64
 42  month_aug                      41188 non-null  int64
 43  month_dec                      41188 non-null  int64
 44  month_jul                      41188 non-null  int64
 45  month_jun                      41188 non-null  int64
 46  month_mar                      41188 non-null  int64
 47  month_may                      41188 non-null  int64
 48  month_nov                      41188 non-null  int64
 49  month_oct                      41188 non-null  int64
 50  month_sep                      41188 non-null  int64
```

```
data.describe()
```

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entrepr
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.C
mean	40.02406	2.567593	962.475454	0.172963	0.963217	0.087623	0.253035	0.224677	0.C
std	10.42125	2.770014	186.910907	0.494901	0.188230	0.282749	0.434756	0.417375	0.1
min	17.00000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.C
25%	32.00000	1.000000	999.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.C
50%	38.00000	2.000000	999.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.C
75%	47.00000	3.000000	999.000000	0.000000	1.000000	0.000000	1.000000	0.000000	0.C
max	98.00000	56.000000	999.000000	7.000000	1.000000	1.000000	1.000000	1.000000	1.C

8 rows × 60 columns

check for missing values

```
print("\nMissing Values:")
print(data.isnull().sum())
```

```
Missing Values:
age                              0
campaign                         0
pdays                            0
previous                         0
no_previous_contact              0
not_working                      0
job_admin.                       0
job_blue-collar                  0
job_entrepreneur                 0
job_housemaid                    0
job_management                   0
job_retired                      0
job_self-employed                0
job_services                     0
job_student                      0
job_technician                   0
job_unemployed                   0
job_unknown                      0
marital_divorced                 0
marital_married                  0
marital_single                   0
marital_unknown                  0
education_basic.4y               0
education_basic.6y               0
education_basic.9y               0
education_high.school            0
education_illiterate             0
education_professional.course    0
education_university.degree      0
education_unknown                0
default_no                       0
default_unknown                  0
default_yes                      0
housing_no                       0
housing_unknown                  0
housing_yes                      0
loan_no                          0
loan_unknown                     0
loan_yes                         0
contact_cellular                 0
contact_telephone                0
month_apr                        0
month_aug                        0
month_dec                        0
month_jul                        0
month_jun                        0
month_mar                        0
month_may                        0
month_nov                        0
month_oct                        0
month_sep                        0
day_of_week_fri                  0
day_of_week_mon                  0
day_of_week_thu                  0
day_of_week_tue                  0
day_of_week_wed                  0
```

Conclusion:

- We can see that their are 60 different coloumns in the dataset.
- The datset has values of type int64 only.
- Their are no missing values in the dataset

Step 3: Explorartory Data Analysis

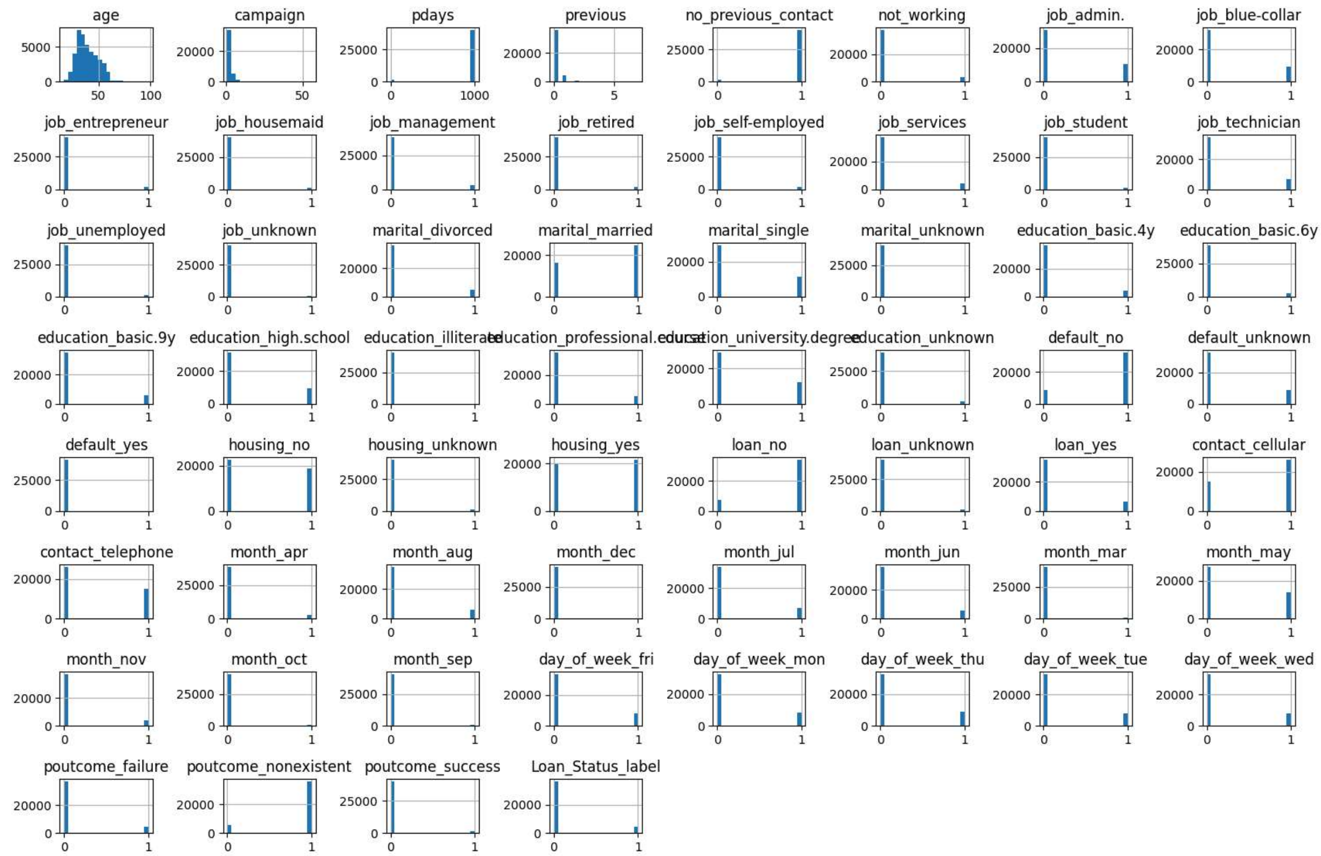
Outlier Detection using Boxplots, Z-Score and Quartiles

```
numerical_features = data.select_dtypes(include=[np.number])
print("Numerical Features:")
print(numerical_features)
```

```
Numerical Features:
       age  campaign  pdays  previous  no_previous_contact  not_working  \
0       56         1    999         0                    1            0
1       57         1    999         0                    1            0
2       37         1    999         0                    1            0
3       40         1    999         0                    1            0
4       56         1    999         0                    1            0
...    ...       ...    ...       ...                  ...          ...
41183   73         1    999         0                    1            1
41184   46         1    999         0                    1            0
41185   56         2    999         0                    1            1
41186   44         1    999         0                    1            0
41187   74         3    999         1                    1            1

       job_admin.  job_blue-collar  job_entrepreneur  job_housemaid  ...  \
0               0                0                 0              1  ...
1               0                0                 0              0  ...
2               0                0                 0              0  ...
3               1                0                 0              0  ...
4               0                0                 0              0  ...
...           ...              ...               ...            ...  ...
41183           0                0                 0              0  ...
41184           0                1                 0              0  ...
41185           0                0                 0              0  ...
41186           0                0                 0              0  ...
41187           0                0                 0              0  ...

       month_sep  day_of_week_fri  day_of_week_mon  day_of_week_thu  \
0              0                0                1                0
1              0                0                1                0
2              0                0                1                0
3              0                0                1                0
4              0                0                1                0
...          ...              ...              ...              ...
41183          0                1                0                0
41184          0                1                0                0
41185          0                1                0                0
41186          0                1                0                0
41187          0                1                0                0

       day_of_week_tue  day_of_week_wed  poutcome_failure  \
0                    0                0                 0
1                    0                0                 0
2                    0                0                 0
3                    0                0                 0
4                    0                0                 0
...                ...              ...               ...
41183                0                0                 0
41184                0                0                 0
41185                0                0                 0
41186                0                0                 0
41187                0                0                 1

       poutcome_nonexistent  poutcome_success  Loan_Status_label
0                         1                 0                  0
1                         1                 0                  0
2                         1                 0                  0
3                         1                 0                  0
```

Visualize the distribution of numerical features

```
numerical_features.hist(figsize=(15, 10), bins=20)
plt.tight_layout()
plt.show()
```



Z-Score method to detect outliers

```
z_scores = np.abs(zscore(numerical_features))
outliers = np.where(z_scores > 3)
print(f"Outliers detected at using zscore: \n{outliers}")
```

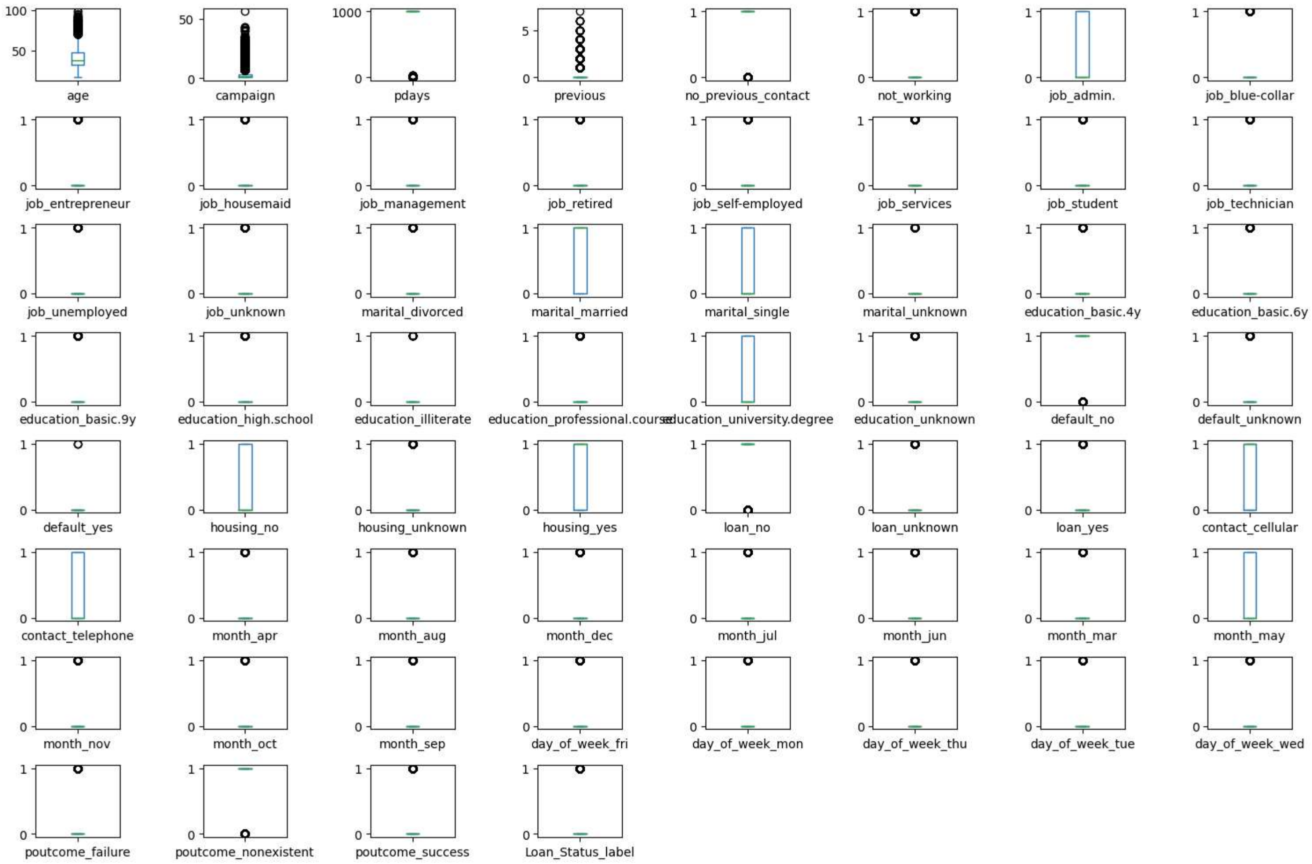
```
Outliers detected at using zscore:
(array([    0,     1,     2, ..., 41187, 41187, 41187]), array([ 9, 13, 13, ...,  5, 11, 48]))
```

given solutuion tells us that these are the rows and coloumns where outliers were detected.

Boxplots

```
# Calculate the number of rows and columns needed to fit all features
num_features = numerical_features.shape[1]
nrows = int(np.ceil(np.sqrt(num_features)))  # Calculate rows for a roughly square layout
ncols = int(np.ceil(num_features / nrows))   # Calculate columns
print(f"\n Rows: {nrows}, Columns: {ncols}")
# Plot the boxplots
numerical_features.plot(kind='box', subplots=True, layout=(nrows, ncols), figsize=(15,10))
print("\n Boxplot of dataset")
plt.tight_layout()
plt.show()
```

```
Rows: 8, Columns: 8

Boxplot of dataset
```



Interquartile Range (IQR) Method

```
Q1 = numerical_features.quantile(0.25)
Q3 = numerical_features.quantile(0.75)
IQR = Q3 - Q1

outliers_iqr = (numerical_features < (Q1 - 1.5 * IQR)) | (numerical_features > (Q3 + 1.5 * IQR))

# Print IQR outliers
print("\nOutliers detected using IQR method:")
for col in numerical_features.columns:
    outliers = numerical_features[outliers_iqr[col]]
    if not outliers.empty:
        print(f"\nOutliers in {col}:\n{outliers}")
```

```
Outliers detected using IQR method:

Outliers in age:
       age  campaign  pdays  previous  no_previous_contact  not_working  \
27713   70         3    999         0                    1            1
27757   76         9    999         0                    1            1
27780   73         1    999         1                    1            1
27800   88         1    999         0                    1            1
```

```
27802   88         2    999         0                   1           1
...    ...       ...    ...       ...                 ...         ...
40986   84         4      3         1                   0           1
40996   81         1    999         2                   1           1
41004   80         1    999         1                   1           1
41183   73         1    999         0                   1           1
41187   74         3    999         1                   1           1

       job_admin.  job_blue-collar  job_entrepreneur  job_housemaid  ...  \
27713           0                0                 0              0  ...
27757           0                0                 0              0  ...
27780           0                0                 0              0  ...
27800           0                0                 0              0  ...
27802           0                0                 0              0  ...
...           ...              ...               ...            ...  ...
40986           0                0                 0              0  ...
40996           0                0                 0              0  ...
41004           0                0                 0              0  ...
41183           0                0                 0              0  ...
41187           0                0                 0              0  ...

       month_sep  day_of_week_fri  day_of_week_mon  day_of_week_thu  \
27713          0                0                1                0
27757          0                0                0                1
27780          0                0                0                0
27800          0                0                0                0
27802          0                0                0                0
...          ...              ...              ...              ...
40986          0                0                1                0
40996          0                0                0                0
41004          0                0                0                1
41183          0                1                0                0
41187          0                1                0                0

       day_of_week_tue  day_of_week_wed  poutcome_failure  \
27713                0                0                 0
27757                0                0                 0
27780                1                0                 1
27800                0                1                 0
27802                0                1                 0
...                ...              ...               ...
40986                0                0                 0
40996                0                1                 1
41004                0                0                 1
41183                0                0                 0
41187                0                0                 1

       poutcome_nonexistent  poutcome_success  Loan_Status_label
```

Handling of outliers-capping of outliers

```
# Define the capping thresholds (1st and 99th percentiles)
lower_cap = numerical_features.quantile(0.01)
upper_cap = numerical_features.quantile(0.99)

# Apply capping
data_capped = data.copy()  # Make a copy of the dataset to cap outliers

for col in numerical_features.columns:
    data_capped[col] = np.where(data_capped[col] < lower_cap[col], lower_cap[col], data_capped[col])
    data_capped[col] = np.where(data_capped[col] > upper_cap[col], upper_cap[col], data_capped[col])

# Show the number of capped values for each feature
capped_values_count = (data_capped != data).sum()
print("Number of capped values per feature:\n", capped_values_count)

# Check the distribution after capping
print("\nData after capping outliers:")
print(data_capped.describe())
```

```
Number of capped values per feature:
 age                            748
campaign                       406
pdays                          102
previous                       310
no_previous_contact              0
not_working                      0
job_admin.                       0
job_blue-collar                  0
job_entrepreneur                 0
job_housemaid                    0
job_management                   0
job_retired                      0
job_self-employed                0
job_services                     0
job_student                      0
job_technician                   0
```

```
job_unemployed                   0
job_unknown                    330
marital_divorced                 0
marital_married                  0
marital_single                   0
marital_unknown                 80
education_basic.4y               0
education_basic.6y               0
education_basic.9y               0
education_high.school            0
education_illiterate            18
education_professional.course    0
education_university.degree      0
education_unknown                0
default_no                       0
default_unknown                  0
default_yes                      3
housing_no                       0
housing_unknown                  0
housing_yes                      0
loan_no                          0
loan_unknown                     0
loan_yes                         0
contact_cellular                 0
contact_telephone                0
month_apr                        0
month_aug                        0
month_dec                      182
month_jul                        0
month_jun                        0
month_mar                        0
month_may                        0
month_nov                        0
month_oct                        0
month_sep                        0
day_of_week_fri                  0
day_of_week_mon                  0
day_of_week_thu                  0
day_of_week_tue                  0
day_of_week_wed                  0
poutcome_failure                 0
```

Step 4: Model Building

Encode Categorical Variables and Scale Numerical Features

```
X = data.drop('Loan_Status_label', axis=1)
y = data['Loan_Status_label']

label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

categorical_cols = X.select_dtypes(include=['object']).columns
numerical_cols = X.select_dtypes(include=[np.number]).columns

numerical_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])

X_preprocessed = preprocessor.fit_transform(X)
```

Split the Data

```
X_train, X_test, y_train, y_test = train_test_split(X_preprocessed, y, test_size=0.3, random_state=42)
```

Model Selection

```
logistic_model = LogisticRegression(random_state=42)
```

```
random_forest_model = RandomForestClassifier(random_state=42)
```

```
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss', random_state=42)
```

Model Training

```
logistic_model.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(random_state=42)
```

```
random_forest_model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
xgb_model.fit(X_train, y_train)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, random_state=42, ...)
```

Model Evaluation

```
y_pred_logistic = logistic_model.predict(X_test)
```

```
y_pred_rf = random_forest_model.predict(X_test)
```

```
y_pred_xgb = xgb_model.predict(X_test)
```

```
print("Logistic Regression Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_logistic))
print(classification_report(y_test, y_pred_logistic))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_logistic))
```

```
Logistic Regression Performance:
Accuracy: 0.8981144290685441
              precision    recall  f1-score   support

           0       0.91      0.99      0.95     10968
           1       0.66      0.19      0.30      1389

    accuracy                           0.90     12357
   macro avg       0.78      0.59      0.62     12357
weighted avg       0.88      0.90      0.87     12357

Confusion Matrix:
 [[10829   139]
 [ 1120   269]]
```

```
print("\nRandom Forest Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
```

```

Random Forest Performance:
Accuracy: 0.8887270373067897
              precision    recall  f1-score   support

           0       0.91      0.97      0.94     10968
           1       0.51      0.25      0.34      1389

    accuracy                           0.89     12357
   macro avg       0.71      0.61      0.64     12357
```

```
weighted avg       0.87      0.89      0.87     12357

Confusion Matrix:
 [[10630   338]
 [ 1037   352]]
```

```
print("\nXGBoost Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_xgb))
print(classification_report(y_test, y_pred_xgb))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
```

```
XGBoost Performance:
Accuracy: 0.8943109168892126
              precision    recall  f1-score   support

           0       0.91      0.98      0.94     10968
           1       0.57      0.24      0.33      1389

    accuracy                           0.89     12357
   macro avg       0.74      0.61      0.64     12357
weighted avg       0.87      0.89      0.87     12357

Confusion Matrix:
 [[10724   244]
 [ 1062   327]]
```

Analysis

Based on Accuracy:

- Logistic Regression has the highest accuracy at 0.90, slightly higher than XGBoost (0.89) and Random Forest (0.89).
- This suggests that Logistic Regression correctly predicts the overall outcome slightly more often.

Based on Precision:

- For Class 1 (the minority class), Logistic Regression has the highest precision at 0.66, followed by XGBoost at 0.57, and Random Forest at 0.51.
- This indicates that when Logistic Regression predicts a positive case (Class 1), it is more likely to be correct compared to the other models.

Based on Recall:

- Class 1 recall is highest with Random Forest and XGBoost at 0.25 and 0.24, respectively.
- Logistic Regression has a recall of only 0.19 for Class 1, meaning it misses more actual positives.
- Class 0 recall is highest with Logistic Regression at 0.99, meaning it correctly identifies almost all negatives.

Based on F1-Score:

- The F1-score for Class 1 is highest for Random Forest at 0.34, slightly better than XGBoost (0.33) and Logistic Regression (0.30).
- F1-Score balances precision and recall, making it a good metric when dealing with imbalanced classes.

Based on Confusion Matrix:

Class 1:

- Logistic Regression has the highest number of false negatives (1,120), meaning it misses many actual positives.
- XGBoost has a slightly lower number of false negatives (1,062) compared to Random Forest (1,037).

Class 0:

- Logistic Regression has the lowest number of false positives (139), indicating better performance in correctly identifying negatives.

From the above given results, ***Random Forest*** might be the best option for this problem, especially if *correctly identifying as many positives as possible* is crucial. However, if you need *higher precision and overall accuracy*, we can opt for ***Logistic Regression***.

Fine Tuning of model developed using XGBoost

```
# Define the hyperparameter space
param_dist = {
    'learning_rate': [0.01, 0.05, 0.1, 0.15, 0.2],
    'n_estimators': np.arange(100, 500, 50),   # Randomly select from 100 to 500 estimators
    'max_depth': np.arange(3, 10, 1),          # Randomly select from depths 3 to 10
    'subsample': [0.6, 0.7, 0.8, 0.9, 1.0],    # Different subsample ratios
    'colsample_bytree': [0.6, 0.7, 0.8, 0.9, 1.0],  # Different feature subsample ratios
    'gamma': [0, 0.1, 0.2, 0.3, 0.4],          # Range of gamma values for regularization
    'reg_alpha': [0, 0.01, 0.05, 0.1],         # L1 regularization
    'reg_lambda': [0.5, 1, 1.5, 2]             # L2 regularization
}
```

using RandomizedSerchCV because the dataset is large

```
# Set up the RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=xgb_model, param_distributions=param_dist,
                                   n_iter=100, cv=5, scoring='accuracy', n_jobs=-1,
                                   verbose=2, random_state=42)
```

```
# Fit the RandomizedSearchCV to the data
random_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
RandomizedSearchCV
estimator: XGBClassifier
XGBClassifier
```

```
# Get the best parameters
best_params = random_search.best_params_
print("Best Parameters:", best_params)
```

```
Best Parameters: {'subsample': 0.6, 'reg_lambda': 0.5, 'reg_alpha': 0.1, 'n_estimators': 450, 'max_depth': 5, 'learning_rate': 0.01,
```

```
# Train the XGBoost model with the best parameters
best_xgb_model = random_search.best_estimator_
```

```
# Predict on the test set
y_pred_best_xgb = best_xgb_model.predict(X_test)
```

```
# Evaluate the tuned model
print("\nTuned XGBoost Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred_best_xgb))
print(classification_report(y_test, y_pred_best_xgb))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_best_xgb))
```

```
Tuned XGBoost Performance:
Accuracy: 0.8990046127700898
              precision    recall  f1-score   support

           0       0.91      0.99      0.95     10968
           1       0.67      0.20      0.31      1389

    accuracy                           0.90     12357
   macro avg       0.79      0.59      0.63     12357
weighted avg       0.88      0.90      0.87     12357

Confusion Matrix:
 [[10831   137]
 [ 1111   278]]
```

Conlsuion:

1. Slight Improvement in Accuracy
2. Improved Precision, Decreased Recall
3. Trade-Off Between Precision and Recall
4. The reduction in false positives suggests the model is better at correctly classifying negatives, which could be valuable if the cost of a false positive is high.

Comparison

1. Accuracy:

   Tuned XGBoost: 0.8990

   Original XGBoost: 0.8943

2. Precision (Class 1):

   Tuned XGBoost: 0.67

   Original XGBoost: 0.57

3. Recall (Class 1):

   Tuned XGBoost: 0.20

   Original XGBoost: 0.24

4. F1-Score (Class 1):

   Tuned XGBoost: 0.31

   Original XGBoost: 0.33

5. Confusion Matrix:

   Tuned XGBoost:

   True Negatives (Class 0): 10,831

   False Positives (Class 0): 137

   False Negatives (Class 1): 1,111

   True Positives (Class 1): 278

   Original XGBoost:

   True Negatives (Class 0): 10,724

   False Positives (Class 0): 244

   False Negatives (Class 1): 1,062

   True Positives (Class 1): 327

Dashboard creation

```
import dash
from dash import dcc, html
import dash_bootstrap_components as dbc
from dash.dependencies import Input, Output
import plotly.express as px
import pandas as pd
import numpy as np
import plotly.figure_factory as ff
import plotly.graph_objs as go

# Load the dataset
file_path = '/loan_detection.csv'  # Adjust the path as needed
data = pd.read_csv(file_path)

# Model Performance Data
model_performance = {
    'Model': ['Tuned XGBoost', 'XGBoost', 'Random Forest', 'Logistic Regression'],
    'Accuracy': [0.8990, 0.8943, 0.8887, 0.8981],
    'Precision Class 1': [0.67, 0.57, 0.51, 0.66],
    'Recall Class 1': [0.20, 0.24, 0.25, 0.19],
    'F1-Score Class 1': [0.31, 0.33, 0.34, 0.30],
}

# Convert model performance data to DataFrame
performance_df = pd.DataFrame(model_performance)

# Initialize the Dash app
app = dash.Dash(__name__, external_stylesheets=[dbc.themes.BOOTSTRAP])

# Layout of the dashboard
app.layout = dbc.Container([
    html.H1("Loan Repayment Prediction Model", style={'textAlign': 'center', 'marginTop': 20, 'marginBottom': 20}),

    # Data Overview and Visualization
    html.Div([
        html.H2("Dataset Overview"),
```

```
        dcc.Graph(
            id='histogram',
            figure=px.histogram(data, x='age', title='Age Distribution')
        ),
        dcc.Graph(
            id='boxplot',
            figure=px.box(data, y='age', title='Age Boxplot')
        )
    ]),

    # Model Performance
    html.Div([
        html.H2("Model Performance"),
        dcc.Graph(
            id='accuracy-bar',
            figure=px.bar(performance_df, x='Model', y='Accuracy', title='Model Accuracy')
        ),
        dcc.Graph(
            id='precision-bar',
            figure=px.bar(performance_df, x='Model', y='Precision Class 1', title='Precision for Class 1')
        ),
        dcc.Graph(
            id='recall-bar',
            figure=px.bar(performance_df, x='Model', y='Recall Class 1', title='Recall for Class 1')
        ),
        dcc.Graph(
            id='f1-bar',
            figure=px.bar(performance_df, x='Model', y='F1-Score Class 1', title='F1-Score for Class 1')
        )
    ]),

    # Confusion Matrices
    html.Div([
        html.H2("Confusion Matrices"),
        dcc.Graph(
            id='tuned-xgb-cm',
            figure=go.Figure(data=go.Heatmap(
                z=[[10831, 137], [1111, 278]],
                x=['Predicted 0', 'Predicted 1'],
                y=['Actual 0', 'Actual 1'],
                colorscale='Greens'
            )).update_layout(title='Tuned XGBoost Confusion Matrix')
        ),
        dcc.Graph(
            id='xgb-cm',
            figure=go.Figure(data=go.Heatmap(
                z=[[10724, 244], [1062, 327]],
                x=['Predicted 0', 'Predicted 1'],
                y=['Actual 0', 'Actual 1'],
                colorscale='Blues'
            )).update_layout(title='XGBoost Confusion Matrix')
        ),
        dcc.Graph(
            id='rf-cm',
            figure=go.Figure(data=go.Heatmap(
                z=[[10630, 338], [1037, 352]],
                x=['Predicted 0', 'Predicted 1'],
                y=['Actual 0', 'Actual 1'],
                colorscale='Reds'
            )).update_layout(title='Random Forest Confusion Matrix')
        ),
        dcc.Graph(
            id='lr-cm',
            figure=go.Figure(data=go.Heatmap(
                z=[[10829, 139], [1120, 269]],
                x=['Predicted 0', 'Predicted 1'],
                y=['Actual 0', 'Actual 1'],
                colorscale='Purples'
            )).update_layout(title='Logistic Regression Confusion Matrix')
        )
    ]),

    # Conclusions
    html.Div([
        html.H2("Conclusions"),
        html.P("""
        Based on the analysis:
        - **Accuracy**: Logistic Regression has the highest accuracy, but all models are close.
        - **Precision**: Logistic Regression and Tuned XGBoost perform well for precision in Class 1.
        - **Recall**: Random Forest and XGBoost have better recall for Class 1.
        - **F1-Score**: Random Forest slightly edges out others in balancing precision and recall.
        """)
    ])
```

```
], fluid=True)

# Run the Dash app
if __name__ == '__main__':
    app.run_server(debug=True)
```