```
In [12]: import pandas as pd
         import numpy as np
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler, LabelEncoder
         from sklearn.linear_model import LogisticRegression
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.metrics import accuracy_score, classification_report
In [13]: df = pd.read_csv(r"C:\Users\KUMALIKA\OneDrive\Desktop\Woxsen_Academics\Term_1\Managerial Communication\loan_data.csv", encoding="ISO-8859-1")
In [14]: df
Out[14]:
               credit.policy
                                                                         dti fico days.with.cr.line revol.bal revol.util inq.last.6mths delinq.2yrs pub.rec not.fully.paid
                                  purpose int.rate installment log.annual.inc
                                                    829.10
                                                             11.350407 19.48 737
                                                                                   5639.958333
                                                                                                28854
                                                                                                         52.1
                       1 debt_consolidation 0.1189
                                                             11.082143 14.29 707
                                                                                                          76.7
                                credit_card 0.1071
                                                   228.22
                                                                                   2760.000000
                                                                                                33623
            2
                      1 debt_consolidation 0.1357
                                                    366.86
                                                             10.373491 11.63 682
                                                                                   4710.000000
                                                                                                 3511
                                                                                                         25.6
                       1 debt_consolidation 0.1008
                                                    162.34
                                                             11.350407 8.10 712
                                                                                   2699.958333
                                                                                                33667
                                                                                                          73.2
            4
                                credit_card 0.1426
                                                    102.92
                                                             11.299732 14.97 667
                                                                                   4066.000000
                                                                                                 4740
                                                                                                         39.5
                                                             12.180755 10.39 672
                                                                                                         82.1
         9573
                                  all_other 0.1461
                                                   344.76
                                                                                 10474.000000 215372
         9574
                                                             11.141862 0.21 722
                                  all_other 0.1253
                                                    257.70
                                                                                   4380.000000
                                                                                                         82.9
         9575
                      0 debt_consolidation 0.1071
                                                    97.81
                                                             10.596635 13.09 687
                                                                                   3450.041667
                                                                                                10036
                                                             10.819778 19.18 692
                                                                                                          3.2
         9576
                      0 home_improvement 0.1600
                                                    351.58
                                                                                   1800.000000
                      0 debt_consolidation 0.1392
         9577
                                                   853.43
                                                             11.264464 16.28 732
                                                                                  4740.000000
                                                                                                37879
                                                                                                         57.0
         9578 rows × 14 columns
In [15]: le = LabelEncoder()
         df['purpose'] = le.fit_transform(df['purpose'])
In [16]: X = df.drop('not.fully.paid', axis=1)
         y = df['not.fully.paid']
In [17]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
In [18]: scaler = StandardScaler()
         X_train_scaled = scaler.fit_transform(X_train)
         X_test_scaled = scaler.transform(X_test)
In [20]: log_reg = LogisticRegression()
         log_reg.fit(X_train_scaled, y_train)
         y_pred_log = log_reg.predict(X_test_scaled)
In [21]: y_pred = log_reg.predict(X_test_scaled)
         print("=== Model Evaluation ===")
         print("Accuracy:", accuracy_score(y_test, y_pred))
         print(classification_report(y_test, y_pred))
        === Model Evaluation ===
        Accuracy: 0.8392484342379958
                      precision recall f1-score support
                           0.84
                                    1.00
                                               0.91
                                                         1611
                                               0.03
                                                          305
                                                         1916
                                               0.84
            accuracy
                                               0.47
                                                         1916
                           0.61
                                     0.51
           macro avg
                           0.77
                                    0.84
                                               0.77
                                                         1916
        weighted avg
In [22]: print("\n=== User Loan Application ===")
         user_input = {
             'credit.policy': 1,
             'purpose': 'credit_card',
             'int.rate': 0.12,
             'installment': 200.0,
             'log.annual.inc': 10.5,
             'dti': 15.0,
             'fico': 700,
             'days.with.cr.line': 4000,
             'revol.bal': 5000,
             'revol.util': 40.0,
             'inq.last.6mths': 1,
             'delinq.2yrs': 0,
             'pub.rec': 0
        === User Loan Application ===
In [23]: user_input['purpose'] = le.transform([user_input['purpose']])[0]
In [24]: user_df = pd.DataFrame([user_input])
         user_scaled = scaler.transform(user_df)
In [25]: prediction = log_reg.predict(user_scaled)[0]
         prediction_proba = log_reg.predict_proba(user_scaled)[0][1]
In [26]: print("\n=== Prediction Result ===")
         if prediction == 1:
             print(" The applicant is likely NOT to fully pay the loan.")
         else:
             print(" The applicant is likely to fully pay the loan.")
         print(f"Probability of NOT fully paying: {prediction_proba:.2f}")
        === Prediction Result ===
         The applicant is likely to fully pay the loan.
        Probability of NOT fully paying: 0.13
In [27]: dtree = DecisionTreeClassifier()
         dtree.fit(X_train, y_train)
         y_pred_tree = dtree.predict(X_test)
In [28]: print("=== Logistic Regression ===")
         print("Accuracy:", accuracy_score(y_test, y_pred_log))
         print(classification_report(y_test, y_pred_log))
         print("\n=== Decision Tree ===")
         print("Accuracy:", accuracy_score(y_test, y_pred_tree))
         print(classification_report(y_test, y_pred_tree))
        === Logistic Regression ===
        Accuracy: 0.8392484342379958
                      precision recall f1-score support
                                                         1611
                                     1.00
                           0.84
                                               0.91
                           0.38
                                     0.02
                                               0.03
                                                          305
                                                         1916
                                               0.84
            accuracy
                                    0.51
                                                         1916
           macro avg
                                               0.47
        weighted avg
                                    0.84
                                               0.77
                                                         1916
          = Decision Tree ===
        Accuracy: 0.7494780793319415
                                  recall f1-score support
                      precision
                                     0.84
                                               0.85
                                                         1611
                           0.24
                                     0.26
                                               0.25
                                                          305
                                               0.75
                                                         1916
            accuracy
                           0.55
                                     0.55
           macro avg
                                               0.55
                                                         1916
                           0.76
                                    0.75
                                               0.75
                                                         1916
        weighted avg
In [20]: import pandas as pd
         import numpy as np
         import gradio as gr
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler, LabelEncoder
         from sklearn.linear_model import LogisticRegression
In [21]: df = pd.read_csv("loan_data.csv", encoding="ISO-8859-1")
In [22]: df
Out[22]:
                                  purpose int.rate installment log.annual.inc
                                                                         dti fico days.with.cr.line revol.bal revol.util inq.last.6mths delinq.2yrs pub.rec not.fully.paid
               credit.policy
                                                                                                         52.1
                                                   829.10
                       1 debt_consolidation 0.1189
                                                             11.350407 19.48 737
                                                                                   5639.958333
                                                                                                28854
                                credit_card 0.1071
                                                   228.22
                                                             11.082143 14.29 707
                                                                                   2760.000000
                                                                                                33623
                                                                                                          76.7
            2
                                                    366.86
                                                                                                 3511
                                                                                                         25.6
                       1 debt_consolidation 0.1357
                                                             10.373491 11.63 682
                                                                                   4710.000000
                                                    162.34
                                                             11.350407 8.10 712
                                                                                   2699.958333
                                                                                                33667
                                                                                                          73.2
            3
                      1 debt_consolidation 0.1008
            4
                                credit_card 0.1426
                                                    102.92
                                                             11.299732 14.97 667
                                                                                   4066.000000
                                                                                                 4740
                                                                                                         39.5
                                                             12.180755 10.39 672
                                                                                                         82.1
         9573
                                  all_other 0.1461
                                                   344.76
                                                                                 10474.000000
                                                                                               215372
                                                             11.141862 0.21 722
         9574
                                  all_other 0.1253
                                                   257.70
                                                                                   4380.000000
         9575
                      0 debt_consolidation 0.1071
                                                    97.81
                                                             10.596635 13.09 687
                                                                                   3450.041667
                                                                                                10036
                                                                                                         82.9
         9576
                      0 home_improvement 0.1600
                                                    351.58
                                                             10.819778 19.18 692
                                                                                   1800.000000
                                                                                  4740.000000 37879
                                                                                                         57.0
         9577
                                                   853.43
                                                             11.264464 16.28 732
                      0 debt_consolidation 0.1392
         9578 rows × 14 columns
In [23]: le = LabelEncoder()
         df["purpose"] = le.fit_transform(df["purpose"])
In [24]: X = df.drop("not.fully.paid", axis=1)
         y = df["not.fully.paid"]
In [25]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
In [26]: scaler = StandardScaler()
         X_train_scaled = scaler.fit_transform(X_train)
In [27]: log_reg = LogisticRegression()
         log_reg.fit(X_train_scaled, y_train)
Out[27]:
         ▼ LogisticRegression
         LogisticRegression()
In [28]: def predict_loan(credit_policy, purpose, int_rate, installment, log_annual_inc, dti, fico,
                          days_with_cr_line, revol_bal, revol_util, inq_last_6mths, delinq_2yrs, pub_rec):
             user_input = {
                 'credit.policy': 1 if credit_policy == "Yes" else 0,
                 'purpose': le.transform([purpose])[0],
                 'int.rate': float(int_rate),
                 'installment': float(installment),
                 'log.annual.inc': float(log_annual_inc),
                 'dti': float(dti),
                 'fico': int(fico),
                 'days.with.cr.line': int(days_with_cr_line),
                 'revol.bal': int(revol_bal),
                 'revol.util': float(revol_util),
                 'inq.last.6mths': int(inq_last_6mths),
                 'delinq.2yrs': int(delinq_2yrs),
                 'pub.rec': int(pub_rec)
             df_input = pd.DataFrame([user_input])
             scaled = scaler.transform(df_input)
             pred = log_reg.predict(scaled)[0]
             prob = log_reg.predict_proba(scaled)[0][1]
             if pred == 1:
                 result = " The applicant is likely NOT to fully pay the loan."
                 result = " The applicant is likely to fully pay the loan."
             return f"{result}\n Probability of NOT fully paying: {prob:.2f}"
In [29]: interface = gr.Interface(
             fn=predict_loan,
             inputs=[
                 gr.Radio(["Yes", "No"], label="Credit Policy"),
                 gr.Radio(list(le.classes_), label="Loan Purpose"),
                 gr.Radio(["0.10", "0.12", "0.14", "0.16", "0.18"], label="Interest Rate"),
                 gr.Radio(["100", "200", "300", "400", "500"], label="Installment"),
                 gr.Radio(["9.0", "10.0", "10.5", "11.0", "12.0"], label="Log Annual Income"),
                 gr.Radio(["10", "15", "20", "25", "30"], label="DTI"),
                 gr.Radio(["650", "680", "700", "720", "750"], label="FICO"),
                 gr.Radio(["2000", "3000", "4000", "5000", "6000"], label="Days with Credit Line"),
                 gr.Radio(["1000", "3000", "5000", "7000", "9000"], label="Revolving Balance"),
                 gr.Radio(["20", "40", "60", "80", "100"], label="Revol Util %"),
                 gr.Radio(["0", "1", "2", "3", "4"], label="Inquiries Last 6 Months"),
                 gr.Radio(["0", "1", "2"], label="Delinquencies Last 2 Years"),
                 gr.Radio(["0", "1", "2"], label="Public Records")
             ],
             outputs="text",
             title="Loan Repayment Prediction",
             description="Will the applicant fully repay the loan? Select options and click Predict."
In [30]: interface.launch()
        * Running on local URL: http://127.0.0.1:7862
        * To create a public link, set `share=True` in `launch()`.
```

Out[30]: