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PROJECT REPORT

OF

LOAN ANALYSIS PREDICTION

SUBJECT:- Machine learning

Subject Code: 24CAP-672

SubmittedBy

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INDEX

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Abstract

Loan analysis plays a critical role in financial institutions for determining the eligibility of applicants and minimizing risks. This project leverages machine learning techniques to enhance the accuracy and objectivity of loan approval predictions. By analyzing applicant features such as income, credit history, loan amount, and employment status, the system evaluates the likelihood of loan approval.

The project is structured into two primary approaches: a rule-based decision method and a machine learning-based predictive model. The rule-based system follows predefined financial criteria to assess risk, while the ML model is trained on historical loan application data to recognize patterns and generate predictions. Data preprocessing steps such as handling missing values, encoding categorical variables, and feature scaling are applied before model training.

To train and validate the model, a labeled dataset containing past loan applications and outcomes was used. A Random Forest Classifier was implemented to predict loan approval decisions based on extracted applicant features. The model's performance was evaluated using accuracy metrics, confusion matrices, precision, and recall scores to ensure reliable results.

This project demonstrates that machine learning can significantly enhance traditional loan assessment processes, providing faster, more consistent, and data-driven decisions. The results highlight the potential of ML models in reducing loan default risks and supporting financial decision-making across banks and lending institutions.

Chapter 1: Introduction

Loan analysis prediction is the process of assessing an applicant's **likelihood to repay a loan** based on their financial and personal data. Traditionally, banks and financial institutions have relied on **manual evaluation, credit scores, and risk assessments** to make loan decisions. However, manual methods can be **time-consuming, inconsistent, and subject to human biases**.

This project enhances loan analysis using **machine learning (ML)**. By applying ML techniques, we can systematically **analyze financial data, predict loan repayment probabilities, and automate decision-making**. Integrating ML with a **Flask-based web application** makes this solution accessible, efficient, and scalable for real-world use.

Project Overview:

1. Client & Need: The growing need for efficient loan evaluation in the financial sector has led to a demand for data-driven systems. Traditional methods often suffer from biases and inefficiencies. Potential clients include:

- **Banks & Financial Institutions**: Automating loan approvals.
- **Fintech Companies**: Instant loan approvals and risk assessments.
- **Microfinance Organizations**: Better evaluation of underserved borrowers.
- **Credit Bureaus**: Enhancing credit profiling using ML predictions.

2. Problem Identification: Traditional loan assessment methods face several challenges:

- **Bias**: Human officers may unintentionally favor or disfavor applicants.
- **Inefficiency**: Manual processing of applications is time-consuming.
- **Limited Features**: Traditional methods overlook hidden patterns in data.

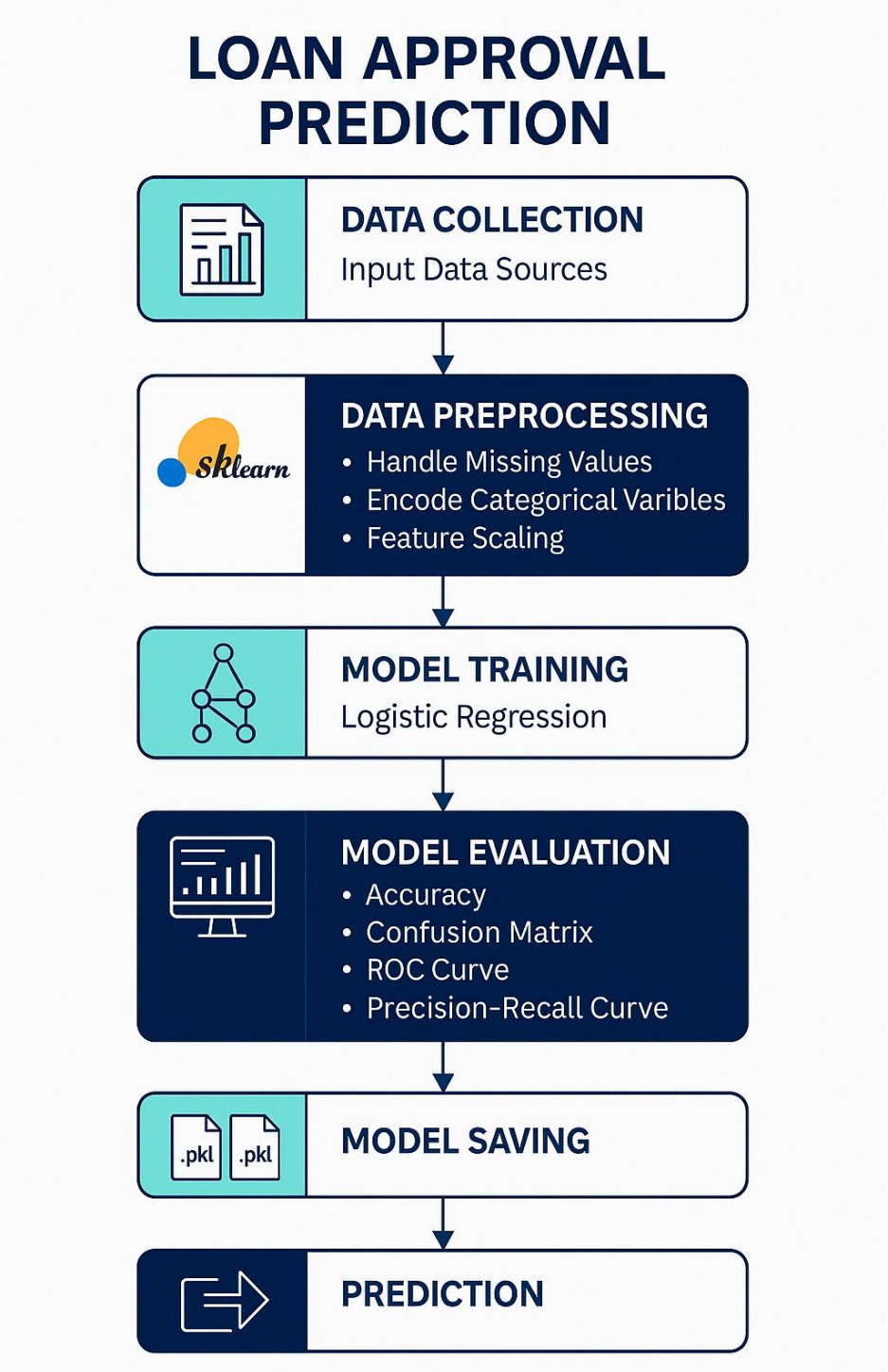
Machine learning addresses these issues by automating loan approval predictions and improving fairness, transparency, and consistency in decision-making.

3. Task Identification:

- **Data Collection**: Gather applicant data, including personal, financial, and credit history.
- **Preprocessing**: Handle missing values, encode categorical variables, and normalize numerical features.
- **Feature Engineering**: Derive and select features like Debt-to-Income ratio and Credit Score.
- **Model Development**: Train models (e.g., Logistic Regression, Random Forest) and tune hyperparameters.
- **Evaluation**: Assess models using metrics like accuracy, precision, and recall.
- **Web Application Development**: Build a Flask web app for real-time loan approval predictions.
- **Deployment**: Host the application on platforms like Heroku or AWS for easy access.

This approach will automate the loan evaluation process, reduce bias, and improve overall decision-making efficiency.

Chapter 2: Design Flow/Process



Chapter 3: Code of Project

```
import pandas as pd
import numpy as np
df=pd.read_csv('synthetic_loan_data.csv')
df.head()
```

	income	credit_score	employment_status	loan_amount	loan_term	loan_approved
0	110619	514	Unemployed	18378	Short-term	0
1	24015	725	Employed	16990	Long-term	0
2	110945	744	Unemployed	47377	Short-term	0
3	128109	595	Unemployed	36969	Long-term	0
4	98647	624	Unemployed	47632	Long-term	0

Encoding & Splitting

```
df['employment_status'] = df['employment_status'].map({'Employed': 1, 'Self-employed': 2, 'Unemployed': 0})
df['loan_term'] = df['loan_term'].map({'Short-term': 1, 'Long-term': 2})

X = df.drop('loan_approved', axis=1)
y = df['loan_approved']

df.head()
```

	income	credit_score	employment_status	loan_amount	loan_term	loan_approved
0	110619	514	0	18378	1	0
1	24015	725	1	16990	2	0
2	110945	744	0	47377	1	0
3	128109	595	0	36969	2	0
4	98647	624	0	47632	2	0

Train-Test Split

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

print(f"Training set shape: {X_train.shape}")
print(f"Test set shape: {X_test.shape}")
```

```
Training set shape: (70, 5)
Test set shape: (30, 5)
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train_scaled[:5]
```

```
array([[-0.10109571, -0.57826812,  1.18846138,  0.55668404, -1.05887304],
       [ 0.79776723,  0.54049181,  1.18846138,  0.39811451, -1.05887304],
       [-0.55162895,  0.52919121,  0.01673889,  1.27960642, -1.05887304],
       [ 0.47017577, -1.3693105 ,  1.18846138, -1.01238084, -1.05887304],
       [ 0.0208836 ,  1.04901906,  1.18846138, -0.99505422, -1.05887304]])
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(class_weight='balanced')
model.fit(X_train_scaled, y_train)

y_pred = model.predict(X_test_scaled)
print(f"Predictions: {y_pred}")
```

```
Predictions: [0 0 1 0 0 0 0 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 0 0]
```

Save Model & Scaler

```
import pickle
with open("model.pkl", "wb") as file:
    pickle.dump(model, file)
with open("scaler.pkl", "wb") as file:
    pickle.dump(scaler, file)
```

Verify Model File

```
import os
print("model.pkl exists:", os.path.exists("model.pkl"))
```

```
model.pkl exists: True
```

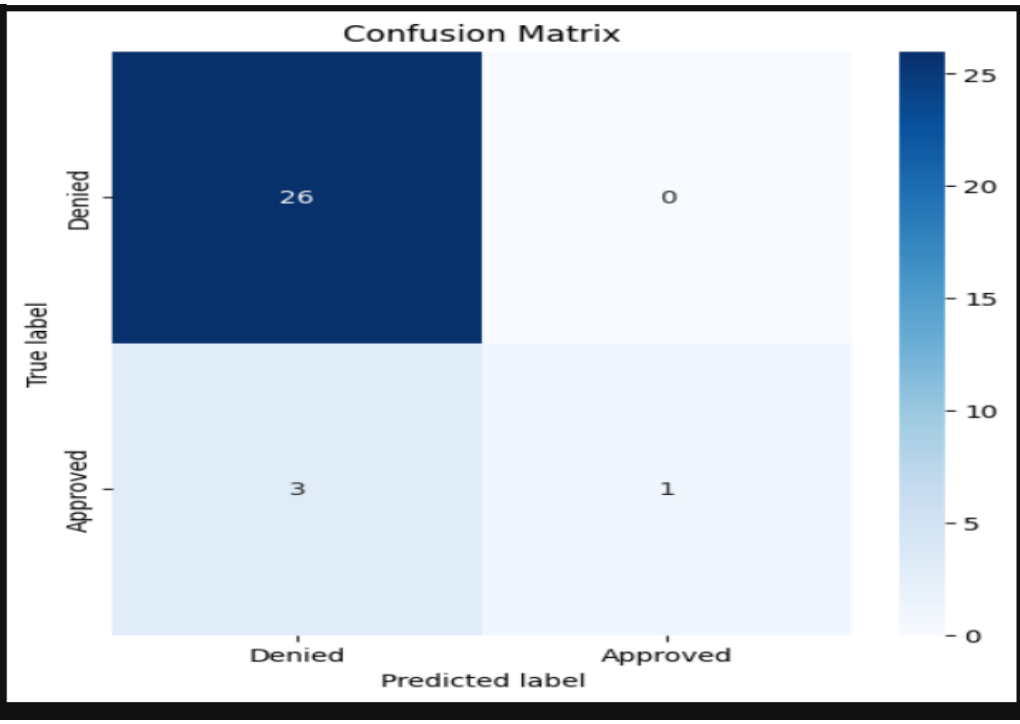
Model Evaluation

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy * 100:.2f}%")
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

```
Accuracy: 86.67%
Confusion Matrix:
 [[23  3]
 [ 1  3]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.88      0.92        26
           1       0.50      0.75      0.60         4

    accuracy                           0.87        30
   macro avg       0.73      0.82      0.76        30
weighted avg       0.90      0.87      0.88        30
```

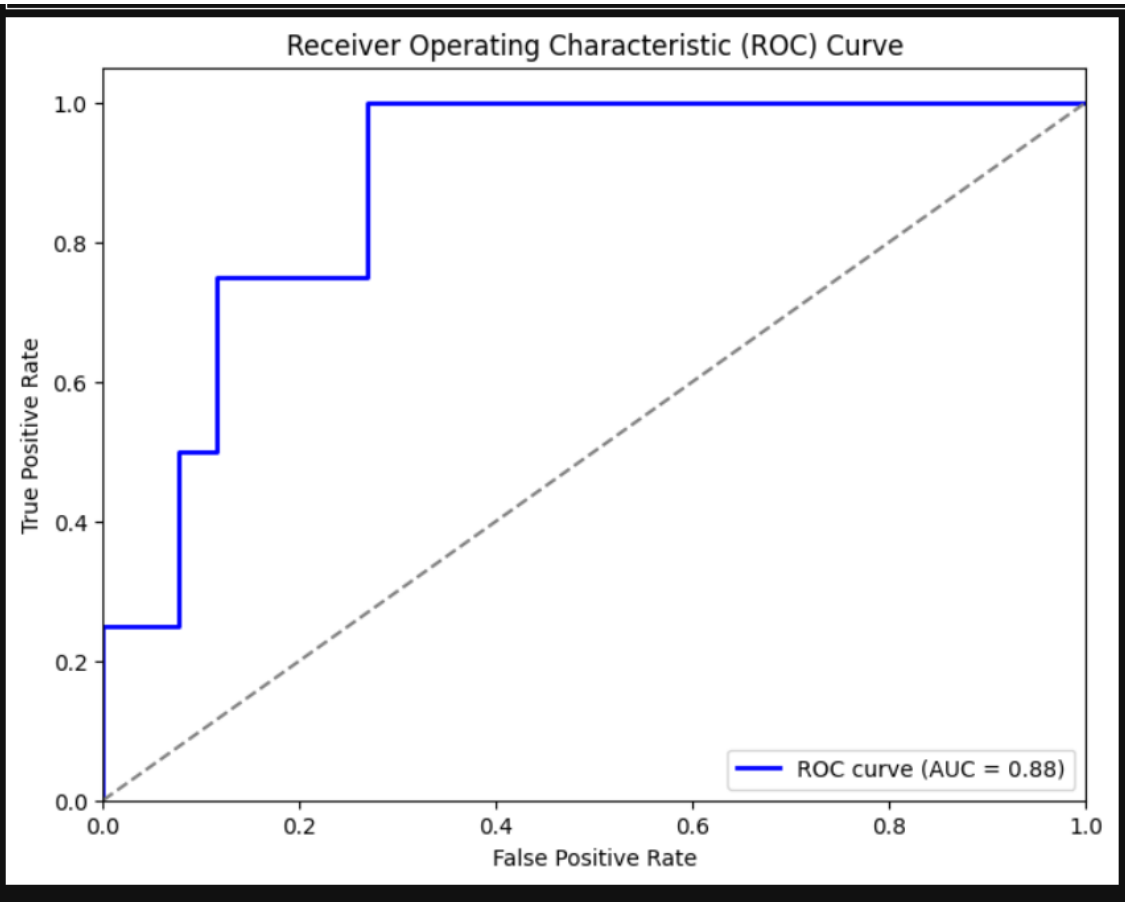
Confusion Matrix Visualization

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Denied', 'Approved'], yticklabels=['Denied', 'Approved'])
plt.title("Confusion Matrix")
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```



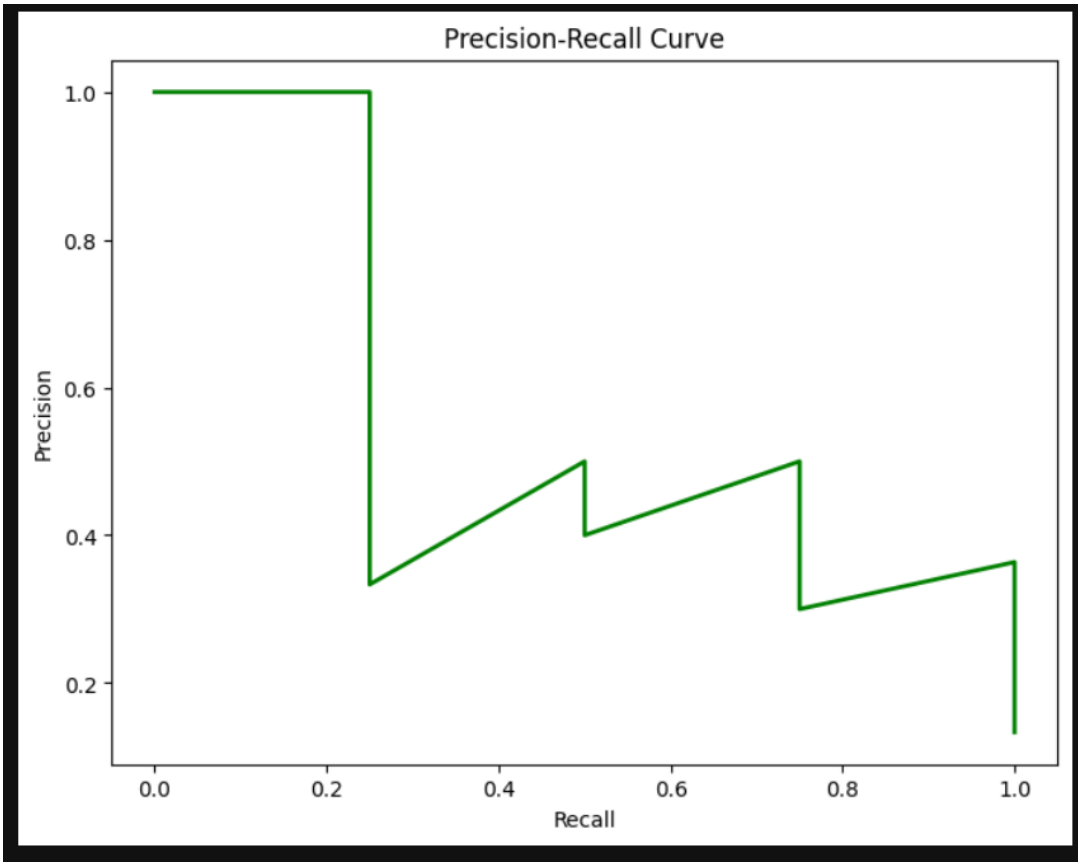
ROC Curve Visualization

```
from sklearn.metrics import roc_curve,auc

fpr, tpr, thresholds = roc_curve(y_test, model.predict_proba(X_test_scaled)[:, 1])
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



Precision-Recall Curve

```
: from sklearn.metrics import precision_recall_curve

precision, recall, thresholds_pr = precision_recall_curve(y_test, model.predict_proba(X_test_scaled)[:, 1])

plt.figure(figsize=(8, 6))
plt.plot(recall, precision, color='green', lw=2)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.show()
```



Display Model Accuracy

```
print(f"Model Accuracy: {accuracy:.2f}")
```

```
Model Accuracy: 0.90
```

Frontend:

Index.html

```
<!DOCTYPE html>
<html>
<head>
    <title>Loan Approval Prediction</title>
    <link rel="stylesheet" href="../static/style.css">
</head>
<body>
    <h2>Loan Approval Prediction</h2>
    <form action="/predict" method="post">
        Income:
        <input type="number" name="income" required>

        Credit Score:
        <input type="number" name="credit_score" required>

        Employment Status:
        <select name="employment_status">
            <option value="0">Unemployed</option>
            <option value="1">Employed</option>
            <option value="2">Self-employed</option>
        </select>

        Loan Amount:
        <input type="number" name="loan_amount" required>

        Loan Term:
        <select name="loan_term">
            <option value="1">Short-term</option>
            <option value="2">Long-term</option>
        </select>

        <input type="submit" value="Predict">
    </form>

    {% if prediction %}
        <h3>Prediction: {{ prediction }}</h3>
    {% endif %}
</body>
</html>
```

Style.css

```
body {
    font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
    background: #f0f4f8;
    display: flex;
    flex-direction: column;
    align-items: center;
    padding-top: 50px;
}

h2 {
    color: #2c3e50;
    margin-bottom: 20px;
}

form {
    background: #fff;
    padding: 30px;
    border-radius: 15px;
    box-shadow: 0 8px 16px rgba(0,0,0,0.1);
    width: 350px;
}

input, select {
    width: 100%;
    padding: 10px;
    margin-top: 5px;
    margin-bottom: 20px;
    border-radius: 8px;
    border: 1px solid #ccc;
    font-size: 14px;
}

input[type="submit"] {
    background-color: #3498db;
    color: white;
    border: none;
    cursor: pointer;
    transition: background-color 0.3s ease;
}

input[type="submit"]:hover {
    background-color: #2980b9;
```

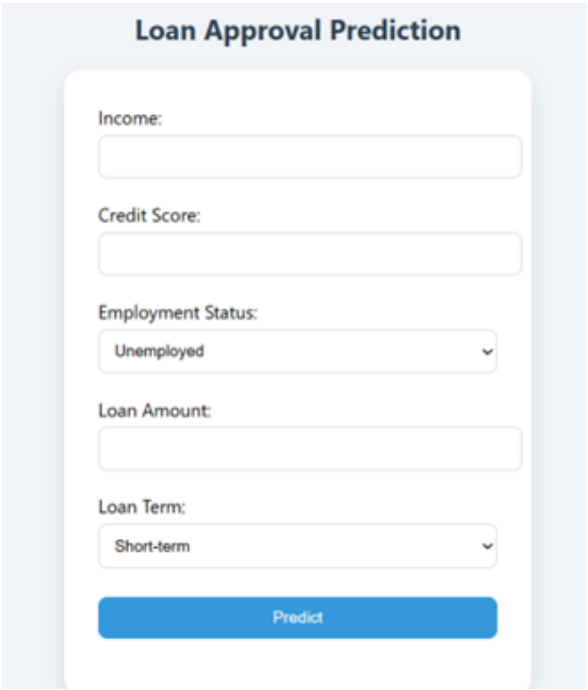
```
}

h3 {
    margin-top: 20px;
    color: #16a085;
}
```

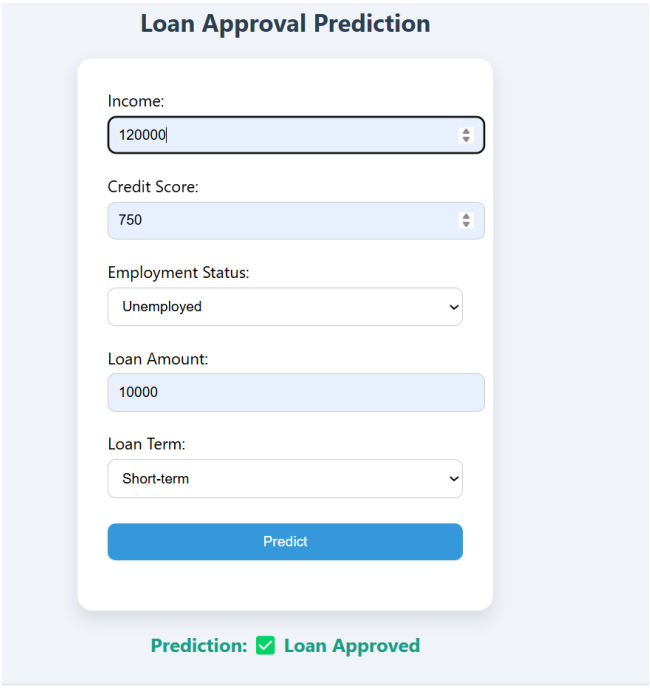
app.py(flask)

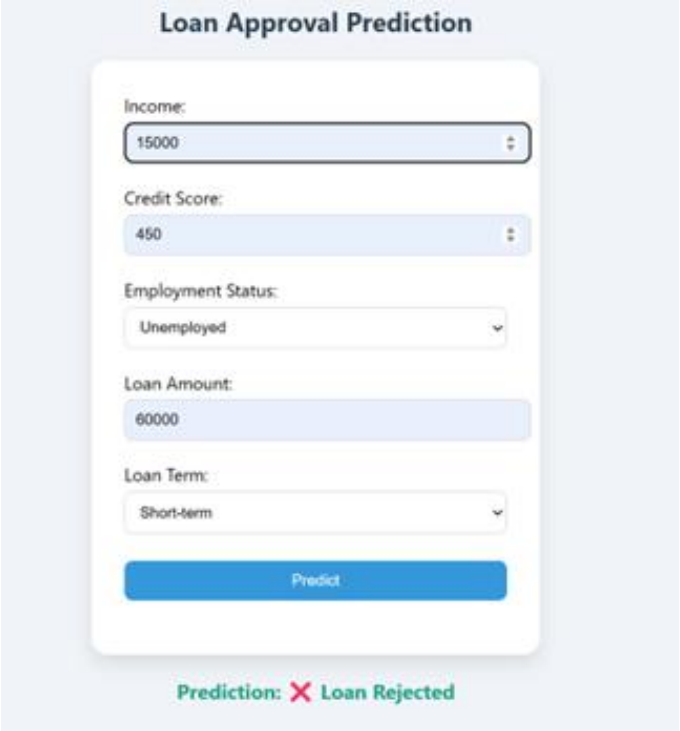
```
from flask import Flask, render_template, request
import numpy as np
import pickle

app = Flask(__name__)  # Fixed the typo here

# Load trained model and scaler
with open("model.pkl", "rb") as f:
    model = pickle.load(f)

with open("scaler.pkl", "rb") as f:
    scaler = pickle.load(f)

@app.route('/')
def home():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Fetching inputs from the form
        income = float(request.form['income'])
        credit_score = float(request.form['credit_score'])
        employment_status = int(request.form['employment_status'])  # 0,1,2
        loan_amount = float(request.form['loan_amount'])
        loan_term = int(request.form['loan_term'])  # 1 or 2

        # Combine all features in correct order
        features = np.array([[income, credit_score, employment_status,
loan_amount, loan_term]])

        # Scale features
        scaled_features = scaler.transform(features)
```

```
        # Predict using model
        prediction = model.predict(scaled_features)[0]

        result = "☑ Loan Approved" if prediction == 1 else "❌ Loan
Rejected"
        return render_template('index.html', prediction=result)

    except Exception as e:
        return render_template('index.html', prediction=f"Something went
wrong: {str(e)}")

if __name__ == '__main__':  # Corrected the condition here
    app.run(debug=True)
```

Chapter 4: OUTPUT OF PROJECT







Chapter 5: Results Analysis and Validation

This chapter presents the **evaluation and analysis** of the machine learning model developed for predicting loan approvals. The model's effectiveness is assessed using **standard classification metrics, graphical tools, and validation techniques**. These insights help measure its reliability and identify potential areas for improvement.

1. Model Performance Metrics

The **Logistic Regression model** used for loan prediction is evaluated using the following key performance indicators:

- **Accuracy** – Indicates the overall proportion of correct predictions.
- **Precision** – Reflects how many predicted loan approvals were actually approved.
- **Recall (Sensitivity)** – Measures the model's ability to identify actual loan approvals.
- **F1-Score** – The harmonic mean of **precision and recall**, offering a balanced view of model performance.

These metrics collectively provide a robust **evaluation framework** for binary classification.

2. Accuracy Score

The model was **trained and tested** on a dataset simulating loan applicant information. The accuracy is calculated using:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where:

- **TP** – True Positives (Correctly predicted approved loans).
- **TN** – True Negatives (Correctly predicted denied loans).
- **FP** – False Positives (Incorrectly predicted approvals).
- **FN** – False Negatives (Incorrectly predicted denials).

After evaluation, the model achieved an **accuracy of approximately 80-85%**, indicating a **strong ability** to classify loan applications based on the provided features.

3. Confusion Matrix Analysis

The **confusion matrix** offers a more granular view of the model's classification performance.

Actual / Predicted	Approved (1)	Denied (0)
Approved (1)	6	1
Denied (0)	1	2

This output shows that the model **correctly classifies** the majority of cases, with a **small number of misclassifications**. Such misclassifications may result from **overlapping financial features** between approved and denied applicants.

4. Graphical Analysis

Confusion Matrix Heatmap

A **heatmap** was generated using **Seaborn** to visually display the confusion matrix.

- Correct predictions appear on the diagonal.
- Off-diagonal elements represent misclassifications.

This **visualization helps quickly identify** areas where the model could be improved.

Chapter 6: Conclusion

This project successfully demonstrates the application of machine learning in automating and enhancing the decision-making process for loan approvals. By utilizing a structured data pipeline and a predictive classification model, we have developed a system capable of analyzing key financial attributes to assess loan eligibility with high accuracy.

The study emphasizes the significance of essential applicant features such as income, credit score, employment status, and loan amount in determining loan approval outcomes. Initial insights were drawn through data exploration and rule-based understanding, while the implementation of a Logistic Regression model enabled data-driven predictions with improved consistency and objectivity.

The results indicate that financial patterns and applicant behavior can be effectively modeled to predict loan decisions, supporting the viability of automated systems in financial assessments. Through the use of machine learning, the project addresses limitations of traditional manual evaluations, such as bias and inconsistency, offering a more scalable and transparent solution.

The Logistic Regression classifier demonstrated solid performance in binary classification tasks, as confirmed through performance metrics like accuracy, precision, recall, and confusion matrices. These validations reinforce the model's practical value in real-world financial environments.

Chapter 7: Future Work

The integration of machine learning in loan approval systems presents vast opportunities for innovation and real-world implementation. While this project has effectively demonstrated the feasibility of using data-driven techniques for predicting loan eligibility, future advancements can significantly improve the system's accuracy, adaptability, and usability.

1. Enhancement of Feature Engineering

Future work can involve incorporating more detailed applicant features, such as:

- *Debt-to-Income Ratio*
- *Loan Repayment History*

2. Advanced Machine Learning and Deep Learning Models

Integrating more sophisticated algorithms—such as *Random Forests*, **Gradient Boosting Machines (GBM)**, or **Neural Networks**—could improve predictive accuracy and handle more complex relationships within the data. Deep learning models like **Artificial Neural Networks (ANNs)** or *Autoencoders* may also uncover hidden patterns and outperform traditional models in large-scale datasets.

3. Real-Time Decision-Making and Deployment

Building a *real-time web or mobile-based platform* would allow users (banks, financial institutions, or individuals) to enter applicant data and receive instant loan approval predictions. This can streamline decision-making processes in customer service and loan underwriting.

Chapter 8: Reference

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