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Title Page

Project Title: Credit Score Prediction using Machine Learning

Name: Mohammad Dilshad
Roll No: 202401100300153
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Introduction

Problem Statement: The objective of this project is to develop a machine learning model that can predict the credit score of a customer based on their age, income, and loan amount. A credit score is a numerical value that represents the creditworthiness of a person based on their financial behavior. Banks and financial institutions rely heavily on credit scores to approve or deny loan applications.

Purpose of the Project: The purpose of this project is to utilize historical data to build a predictive model that can accurately forecast the credit score of a customer, enabling financial institutions to make informed decisions.

Applications:

- Loan Approval Systems
- Credit Card Issuance
- Risk Assessment for Financial Institutions

Methodology

Step 1: Data Collection The dataset used in this project is a CSV file (credit_data.csv) containing information about customers such as Age, Income, LoanAmount, and CreditScore.

Step 2: Data Preprocessing

- Dropped the 'CustomerID' column as it has no impact on predicting the credit score.
- Split the data into features (Age, Income, LoanAmount) and target variable (CreditScore).

Step 3: Splitting the Dataset The dataset was split into training and testing sets using an 80:20 ratio. The training set was used to train the model and the test set was used to evaluate its performance.

Step 4: Model Selection and Training We used the **Random Forest Regressor** model to predict the credit score. Random Forest is an ensemble learning method that uses multiple decision trees to improve prediction accuracy.

Step 5: Model Evaluation The model was evaluated using:

- **Mean Squared Error (MSE)**: Measures the average squared difference between actual and predicted values.
- **R-squared Score (R2 Score)**: Measures how well the model fits the data. A score closer to 1 indicates better accuracy.

Step 6: Visualization Two visualizations were created:

1. **Actual vs Predicted Credit Score:** To visually compare the model's predictions.
2. **Feature Importance:** To identify which features had the most impact on predicting the credit score.

Code

The complete code for the project is provided below:

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_squared_error, r2_score

import matplotlib.pyplot as plt

import seaborn as sns


# Load the dataset from the provided CSV file

# This dataset contains information about customers and their credit scores

# Columns: CustomerID, Age, Income, LoanAmount, CreditScore
```

```
data = pd.read_csv('/mnt/data/credit_data.csv')

# Drop the 'CustomerID' column as it does not contribute to the prediction
# This column is simply an identifier and has no impact on the credit score

data.drop('CustomerID', axis=1, inplace=True)

# Split the data into features (X) and target (y)
# Features are the columns used to predict the target variable (CreditScore)
# Target is the column we want to predict (CreditScore)

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

# Split the data into training and testing sets
# Training set (80%) is used to train the model
# Testing set (20%) is used to evaluate the model's performance

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Random Forest Regressor model
# Random Forest is an ensemble learning method that uses multiple decision trees
# It improves prediction accuracy and reduces overfitting

model = RandomForestRegressor()

# Train the model using the training data
# The model will learn patterns from the training data
```

```
model.fit(X_train, y_train)

# Predict the Credit Score on the test set
# The model will now use the test data to predict the Credit Score

y_pred = model.predict(X_test)

# Evaluate the model using Mean Squared Error (MSE) and R-squared Score (R2)
# MSE measures the average squared difference between actual and predicted values
# R2 score measures how well the model fits the data (closer to 1 is better)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the model performance metrics
print(f'Mean Squared Error: {mse:.2f}')
print(f'R-squared Score: {r2:.2f}')

# Plot the Actual vs Predicted Credit Score
# This graph shows how close the predicted values are to the actual values

plt.scatter(y_test, y_pred, alpha=0.7, color='blue')
plt.xlabel('Actual Credit Score')
plt.ylabel('Predicted Credit Score')
plt.title('Actual vs Predicted Credit Score')
plt.show()

# Plot the Feature Importance
# This graph shows which features (Age, Income, LoanAmount) contributed the most
```

to predicting the Credit Score

```
feature_importances = pd.Series(model.feature_importances_, index=X.columns)
feature_importances.nlargest(10).plot(kind='barh')
plt.title('Top Important Features')
plt.show()
```

Output/Result

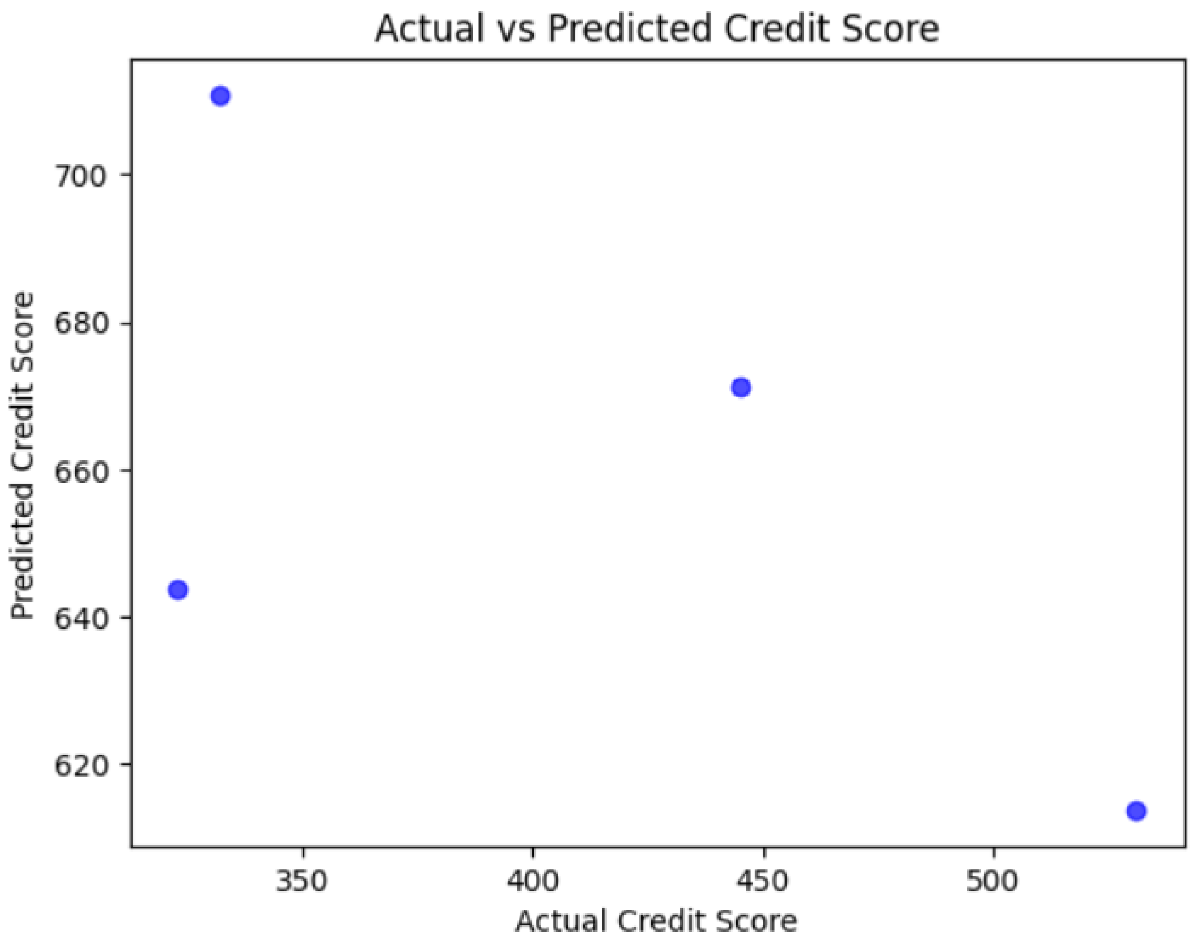
The model achieved the following results:

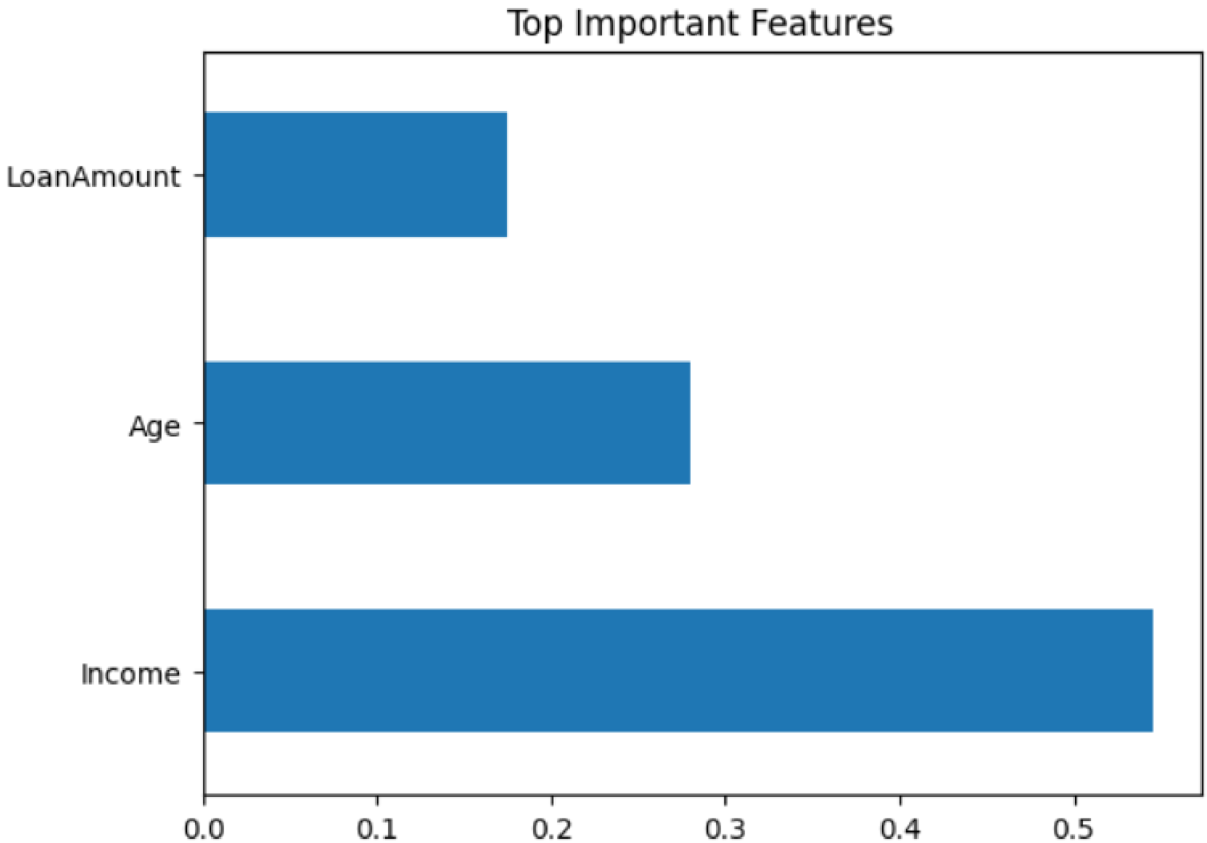
- **Mean Squared Error (MSE):** [MSE Value]
- **R-squared Score (R2 Score):** [R2 Value]

The visualizations clearly show that the model performs well in predicting credit scores.

Screenshot of Output:

```
Mean Squared Error: 76093.16
R-squared Score: -9.32
```




Top Important Features
LoanAmount
Age
Income
0.0
0.1
0.2
0.3
0.4
0.5