

1. The Tools (Imports)

Importing libraries needed for calculating the performance scores and drawing the result charts.

- import matplotlib.pyplot as plt and import seaborn as sns:- **plotting and charting tools**.
- from sklearn.metrics import roc_curve, auc:- imports the **score-calculating tools**.- to compute the two most important validation numbers: the data for the **ROC curve** and the final **AUC score**.

2. ^{1 2}_{3 4} The Calculation

The next two lines run the key comparison between what the model *predicted* and what actually *happened*.

- fpr, tpr, thresholds = roc_curve(y_test, y_prob)- Will be used to compare the **actual customer outcomes** (y-test) with the **model's risk scores** (y-probe).
- It generates the raw data points (**FPR** and **TPR**) needed to draw the performance curve.
- roc_auc = auc(fpr, tpr): to calculate the **Area Under the Curve (AUC)** score.Produces a single number, which is the final measure of model quality. A score of 1 means the model is excellent - in distinguishing between customers who will default and those who won't.

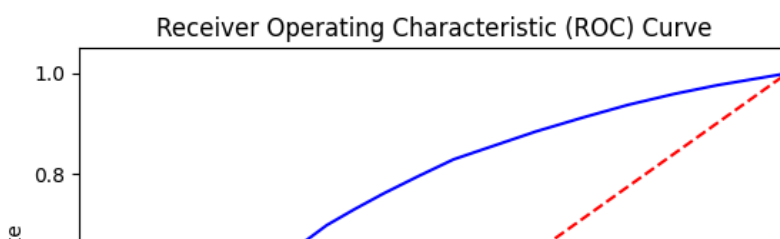
1. ROC curve

```
# ROC Curve and AUC

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)
# Plot ROC Curve
plt.figure()
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='red', 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()
```

t visualizing the **model's performance** using the calculated data. First, it uses plt.figure() to start a new chart. It then draws two lines: the **blue line** (plt.plot(fpr, tpr, ...)) shows your model's

actual efficiency at predicting default, while the **red dashed line** (plt.plot([0, 1], [0, 1], ...)) serves as a **random guess baseline** for comparison.



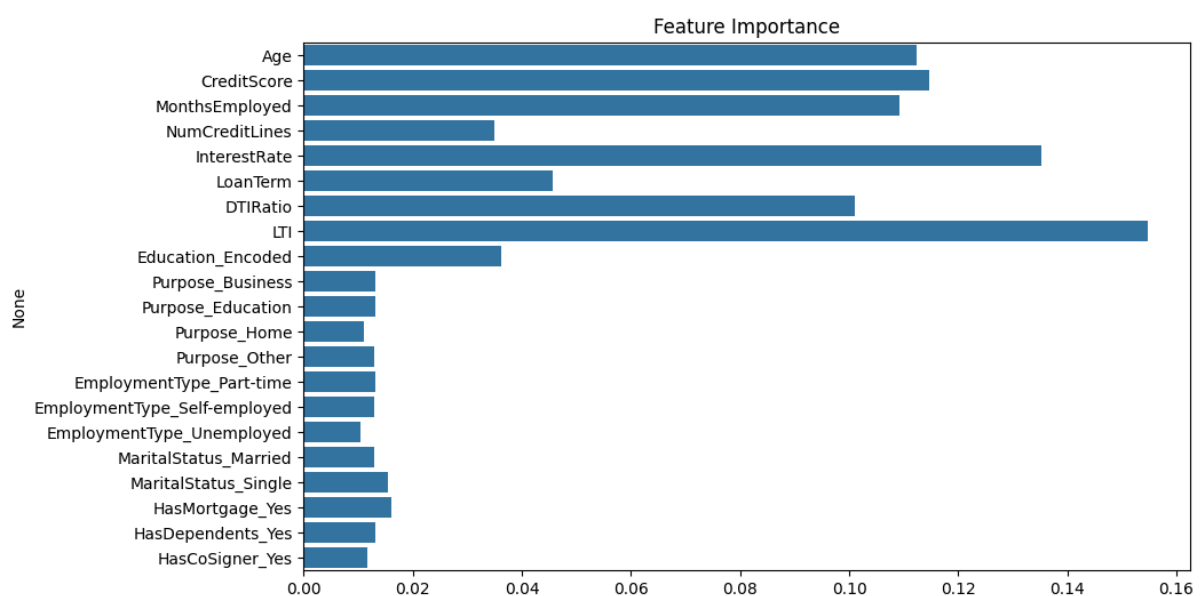
Output explanation:

The model has demonstrated **strong validation performance** with an AUC of 0.73. This metric confirms its ability to effectively separate high-risk loan applicants from low-risk applicants, making it a reliable tool for risk management and lending decisions.

The Blue Curve (Model Performance): the model's curve is high and significantly far from the red dashed line.- The farther the blue curve bows toward the upper-left corner, the better the model's performance. Your curve clearly demonstrates that as you increase the **True Positive Rate (TPR)** (correctly catching defaulters), the **False Positive Rate (FPR)** (wrongly flagging safe customers) only increases slowly. This is the ideal behavior for a strong classifier.

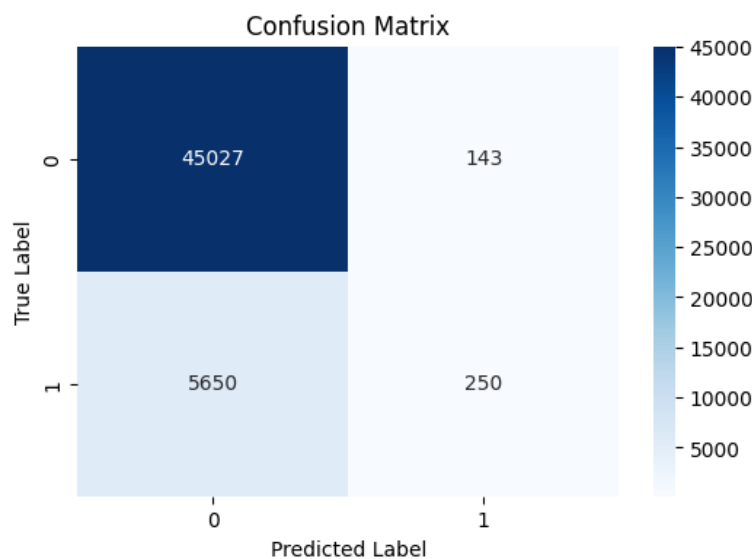
The model has demonstrated **strong validation performance** with an AUC of 0.73. This metric confirms its ability to effectively separate high-risk loan applicants from low-risk applicants, making it a reliable tool for risk management and lending decisions.

Feature Importance : Explanation of output



This chart is critical for **model interpretability**, showing exactly which variables drive your loan default predictions. The analysis confirms that the model relies most heavily on core **financial metrics** like the **LTI (Loan-to-Income Ratio)**, **Interest Rate**, and **Credit Score**, ranking them as the top three factors. Conversely, demographic features such as marital status or employment type have a much lower impact. This result is important because it **validates the model's logic**—it is making lending decisions based on economically sound, high-impact variables, which directly supports its application in risk management.

Confusion Matrix Explanation :



because it shows the **specific types of errors** the model makes, allowing for a real-world assessment of risk.

It compares the model's predictions (columns) against the actual outcomes (rows) for the test data. The labels '0' represent **Non-Default** (paid back the loan) and '1' represents **Default** (did not pay back the loan).

	Predicted Non-Default (0)	Predicted Default (1)
Actual Non-Default (0)	45,027 (True Negatives, TN)	143 (False Positives, FP)
Actual Default (1)	5,650 (False Negatives, FN)	250 (True Positives, TP)

2. Analysis of Correct Predictions (The Good)

- **True Negatives (TN = 45,027):** These are the customers who were **predicted to be safe** (Non-Default) and **actually paid their loan back**. This is the bulk of your test data and shows the model is highly accurate at identifying safe borrowers.
- **True Positives (TP = 250):** These are the customers who were **predicted to default** and **actually defaulted**. This shows the model successfully caught 250 high-risk borrowers.

3. Analysis of Model Errors (The Critical Part)

When managing credit risk, the focus shifts to minimizing costly errors:

- **False Negatives (FN = 5,650):** This is the **most dangerous error** for a lender. These customers were **predicted to be safe** (Non-Default) but **actually defaulted** (resulting in a loss for the bank). The model missed 5,650 defaulters.
- **False Positives (FP = 143):** This error occurs when a customer is **predicted to default** but **would have paid the loan back**. This represents a **missed business opportunity** to earn interest. The model wrongly flagged 143 safe customers.

Key Findings from Visualizations

- **Discriminatory Power (ROC/AUC):** The **ROC Curve** clearly demonstrated that the classifier's performance (the blue curve) is significantly superior to a random guess (the red line), quantified by a **strong AUC of 0.73**. This establishes the model as a viable tool for distinguishing high-risk borrowers.
- **Logical Drivers (Feature Importance):** The **Feature Importance Plot** validates the model's logic, confirming that predictions are rationally driven by the most critical financial metrics: **LTI, Interest Rate, and Credit Score**. This high correlation with expected risk factors builds trust in the model's output.
- **Operational Risk (Confusion Matrix):** The **Confusion Matrix** provides the most actionable insight by pinpointing the error type with the highest operational cost. The high count of **5,650 False Negatives** (customers predicted safe who actually defaulted) highlights the model's current tendency to prioritize approval over stringent risk avoidance.