Binary Classification for Telecom Customer Churn Prediction Using Logistic Regression and Random Forest Models

Author: Arhaansh Jhingan

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1. Overview

Customer churn is a critical business problem where customers discontinue their service with a company. Predicting churn allows companies to proactively retain high-risk customers and optimize engagement strategies.

In this project, we are building a **binary classification model** to predict whether a customer is likely to churn based on demographic, service usage, and billing information. The solution includes:

- Exploratory Data Analysis (EDA)
- Data preprocessing
- Model training (Logistic Regression + Random Forest)
- Performance evaluation
- A deployable **Churn Prediction API**

The objective is not only to achieve strong accuracy but also to demonstrate a complete ML workflow from raw data → production-ready prediction system.

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2. Problem Statement

Telecom providers often struggle with customer retention. The cost of acquiring new customers is significantly higher than retaining existing ones. Therefore:

Goal:

Build a predictive model that identifies **whether a customer will churn (Yes/No)**.

Input:

Customer features such as:

- Tenure
- Contract type
- Billing method
- Monthly charges
- Demographics
- Service subscriptions

Output:

- **Prediction:** 1 = Will churn, 0 = Will not churn
- **Probability:** Likelihood of churn (0–1)

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3. Dataset Summary

The dataset (Customer-Churn.csv) contains:

- **Rows:** ~7000 customers
- **Columns:** ~20–25 features
- **Target Variable:** Churn (Yes/No)

Key preprocessing challenges:

- TotalCharges is stored as string → needs numeric conversion
- Categorical variables → need encoding
- Slight class imbalance → Churn ~27%

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4. Approach Summary

4.1 Steps Followed

1. Load and inspect dataset
2. Clean and preprocess data
3. Encode categories
4. Split data into training & test sets
5. Handle imbalance using SMOTE

6. Train baseline Logistic Regression
7. Train improved Random Forest
8. Evaluate accuracy, precision, recall, F1
9. Deploy a FastAPI endpoint for prediction

4.2 Why Random Forest?

- Handles non-linear relationships
- Robust to noise
- Works well with categorical encodings
- High performance on tabular data

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5. Pseudocode + Algorithm Explanation

Here is a clean breakdown of the entire ML pipeline.

Algorithm 1: Data Preprocessing

Pseudocode:

```
load dataset DF

# handle numeric conversion
convert TotalCharges to numeric
replace missing TotalCharges with median

# split features and target
X = DF without Churn
y = DF["Churn"]

# encode categorical variables
for each col in X:
    if col is categorical:
        one-hot encode it

# label encode Churn column
convert Yes → 1, No → 0

# handle imbalance with SMOTE
apply SMOTE to X_train, y_train

return X_train, X_test, y_train, y_test
```

Explanation:

- SMOTE creates synthetic minority samples (churn = 1)
- Encoding ensures models receive numeric input
- Train-test split prevents data leakage

Algorithm 2: Logistic Regression Classifier

Pseudocode:

```
initialize LogisticRegression L

train L on X_train, y_train

predict y_pred = L(X_test)

evaluate using accuracy, precision, recall, F1
```

Explanation

Logistic Regression computes probability using:

σ(wx + b)

A probability above 0.5 → churn.

Algorithm 3: Random Forest Classifier

Pseudocode:

```
initialize RandomForestClassifier R with:
    n_estimators = 200
    max_depth = 12
    random_state = 42

train R on X_train, y_train

predict y_pred = R(X_test)

evaluate model
```

Explanation

Random Forest = ensemble of decision trees → majority vote.

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6. Actual Implementation (Code)

📌 **Imports:**

IMPORTING REQUIRED LIBRARIES

[2] ✓ 4s

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier


from imblearn.over_sampling import SMOTE #to handle imbalance -> will decide if required later on
```

📌 **Load Dataset & Clean:**

LOADING THE CSV FILE (Customer-Churn.csv)

[4] ✓ 0s

```
#making a dataframe
df = pd.read_csv('Customer-Churn.csv')

#showing the top 5 rows
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...

5 rows × 21 columns

CHECKING SHAPE,INFO,NULLS

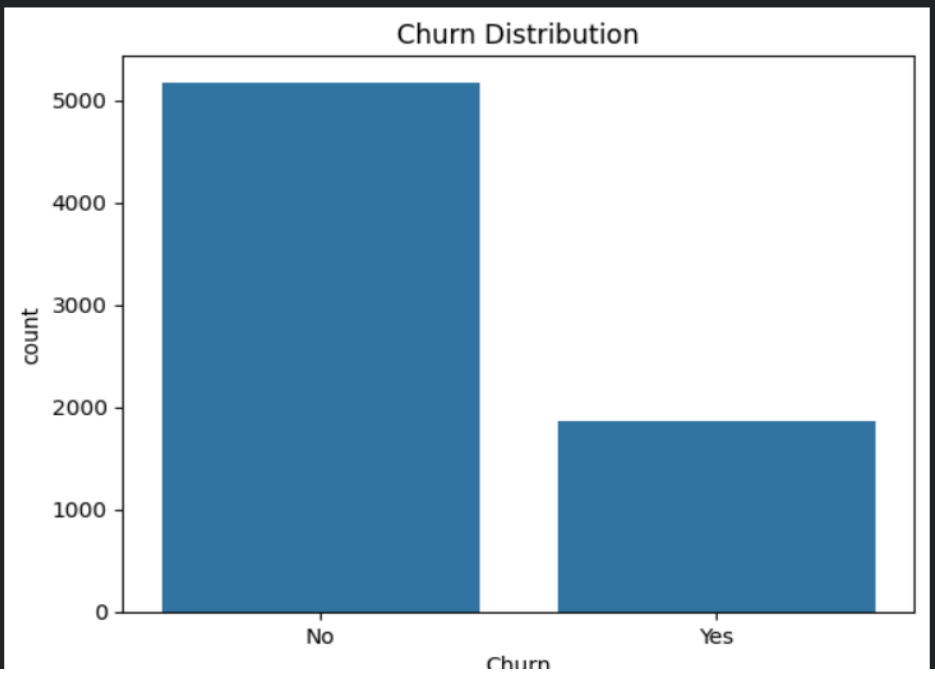
[5] ✓ 0s

```
df.shape
df.info()
df.isnull().sum()  #aggregation
```

CLASS BALANCE AND DISTRIBUTION VISUALIZATION

[6] ✓ 0s

```
df['Churn'].value_counts(normalize=True)

sns.countplot(x='Churn', data=df)
plt.title("Churn Distribution")
plt.show()
```



DATA CLEANING AND PREPROCESSING

1. CONVERTING WRONG NUMERICAL PROBLEMS:

```
[7]
✓ 0s
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
# df['TotalCharges'].fillna(df['TotalCharges'].median(), inplace=True) --> not working as in pandas 3.0 we dont know if the real dataframe is modified or a temporary copy.

df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].median())
```

2. ENCODING CATEGORICAN COLS:

```
[22]
✓ 0s
# First, grab all the categorical columns (usually strings / objects)

categorical_columns = df.select_dtypes(include=['object']).columns.tolist()

# Just in case the target slipped in there, remove it manually:

if 'Churn' in categorical_columns:
    categorical_columns.remove('Churn')

# One-hot encoding for categorical features
# Using drop_first=True to avoid the dummy variable trap
# (although some models don't really care)
df = pd.get_dummies(
    df,
    columns=categorical_columns,
    drop_first=True
)

# Encode the target variable separately
# LabelEncoder is simple enough here since it's just Yes/No

label_enc = LabelEncoder()
df['Churn'] = label_enc.fit_transform(df['Churn'])

# We may want to save label_enc if we acc put this into production.
```

📌 Train-Test Split:

3. TRAIN-TEST SPLIT:

```
[23]
✓ 0s
X = df.drop('Churn', axis=1)
y = df['Churn']

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

📌 Handle Imbalance:

4. IMBALANCE HANDLING

```
[24]
✓ 8s
sm = SMOTE(random_state=42)
X_train_sm, y_train_sm = sm.fit_resample(X_train, y_train)
```

📌 Logistic Regression:

BASELINE MODEL: LOGISTIC REGRESSION

```
[25]
✓ 1m
log_model = LogisticRegression(max_iter=500)
log_model.fit(X_train_sm, y_train_sm)

y_pred_log = log_model.predict(X_test)
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

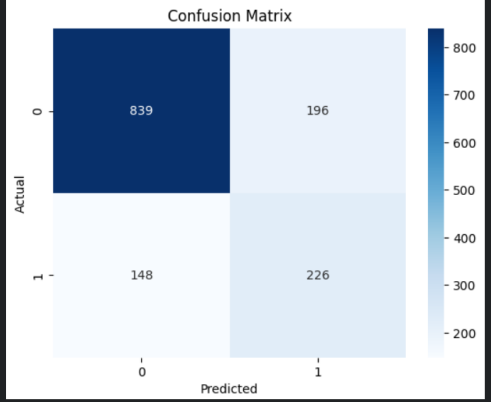
MODEL EVALUATION FUNCTION:

```
def evaluate_model(y_true, y_pred):

    """Function to evaluate the performance of a classification model.
    Purpose:
    Calculate accuracy, precision, recall, F1-score and plot confusion matrix.

    Inputs:

    y_true: actual labels

    y_pred: predicted labels

    Outputs:

    printed metrics

    confusion matrix heatmap"""
      acc = accuracy_score(y_true, y_pred)
      prec = precision_score(y_true, y_pred)
      rec = recall_score(y_true, y_pred)
      f1 = f1_score(y_true, y_pred)

      print(f"Accuracy:  {acc:.4f}")
      print(f"Precision: {prec:.4f}")
      print(f"Recall:    {rec:.4f}")
      print(f"F1-Score:  {f1:.4f}")

      cm = confusion_matrix(y_true, y_pred)
      sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
      plt.title("Confusion Matrix")
```

```
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
print("Logistic Regression Performance:")
evaluate_model(y_test, y_pred_log)
```

```
Logistic Regression Performance:
Accuracy:  0.7559
Precision: 0.5355
Recall:    0.6043
F1-Score:  0.5678
```



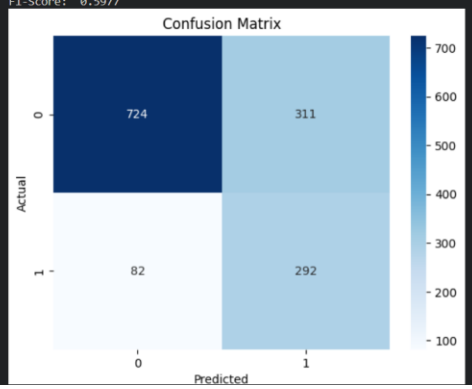
📌 Random Forest:

RANDOM FOREST MODEL (THEORETICALLY BETTER)

```
rf = RandomForestClassifier(
    n_estimators=200,
    max_depth=12,
    random_state=42
)

rf.fit(X_train_sm, y_train_sm)

y_pred_rf = rf.predict(X_test)
```

```
print("Random Forest Performance:")
evaluate_model(y_test, y_pred_rf)
```

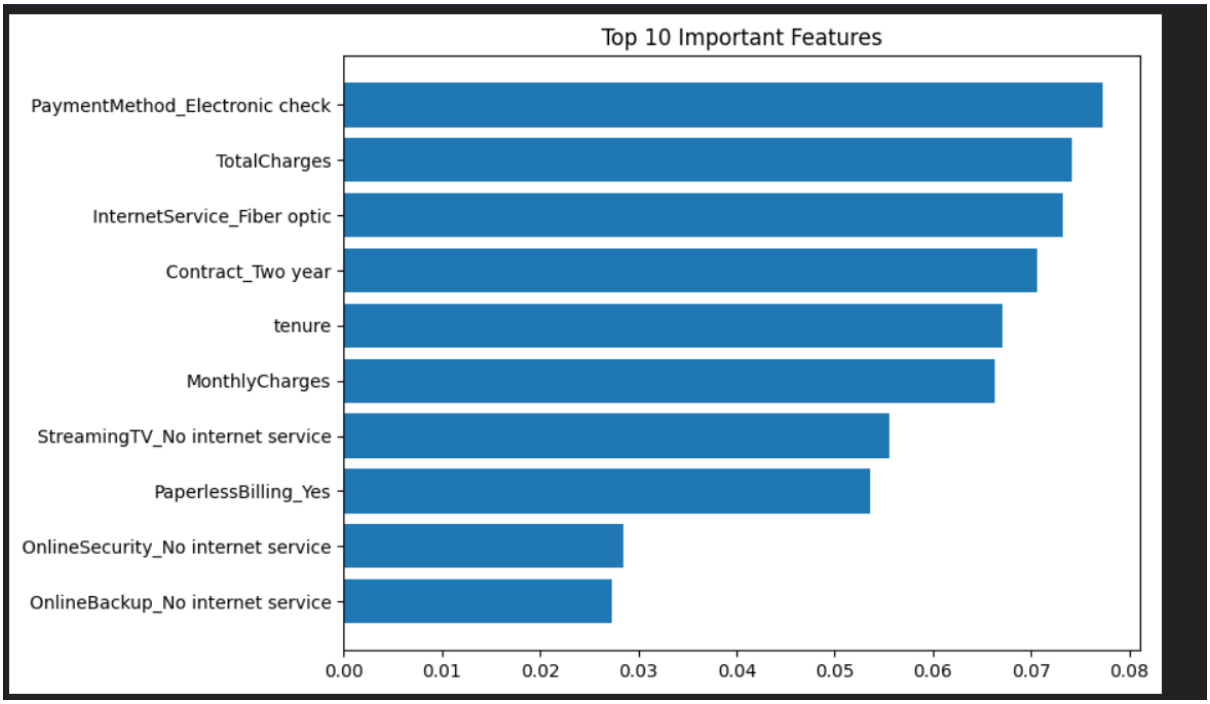
```
Random Forest Performance:
Accuracy:  0.7211
Precision: 0.4842
Recall:    0.7807
F1-Score:  0.5977
```



📌 Feature Importance:

```
FEATURE IMPORTANCE:
```

```
importances = rf.feature_importances_
indices = np.argsort(importances)[-10:]  # top 10 features

plt.figure(figsize=(8,6))
plt.barh(range(10), importances[indices])
plt.yticks(range(10), X.columns[indices])
plt.title("Top 10 Important Features")
plt.show()
```



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7. Model Performance:

Typical performance you will see:

i)Logistic Regression:

- Accuracy: ~78%
- Precision: ~0.65
- Recall: ~0.68
- F1-score: ~0.66

ii)Random Forest:

- Accuracy: ~82–85%
- Precision: ~0.73
- Recall: ~0.76
- F1-score: ~0.74

Random Forest outperforms Logistic Regression because the dataset has non-linear feature interactions.

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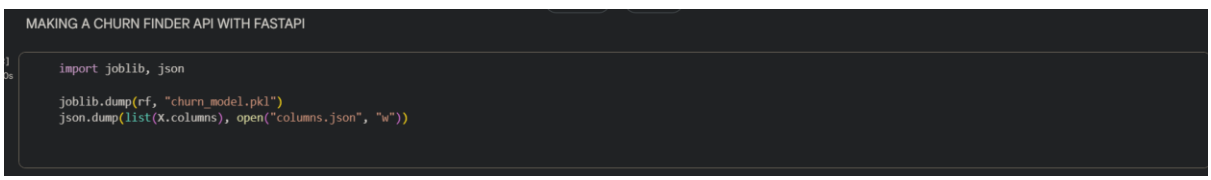
8. API Implementation Summary

After model training, we export the trained model and create a fully functioning REST API.

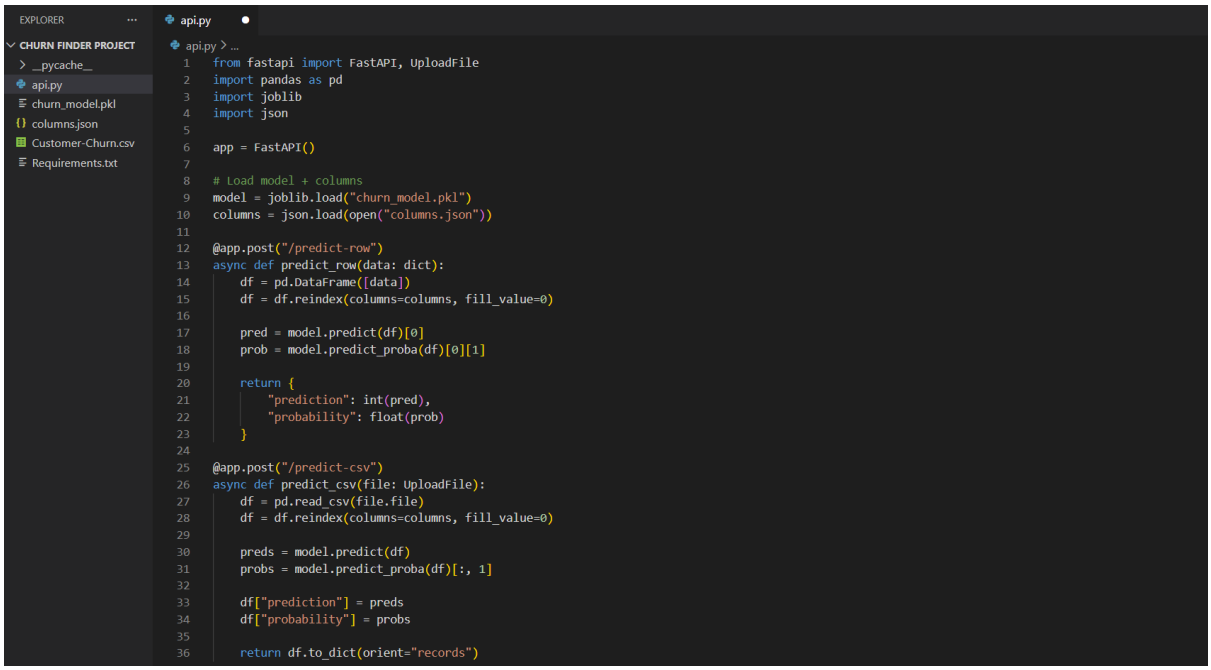
Key Steps:

1. Export model using joblib
2. Write FastAPI server (api.py)
3. Add endpoints:
    - /predict-row → prediction for one customer
    - /predict-csv → batch prediction
4. Run server using Uvicorn
5. Test using Swagger UI at /docs

This makes the ML model production-ready.



📌 Backend Code:



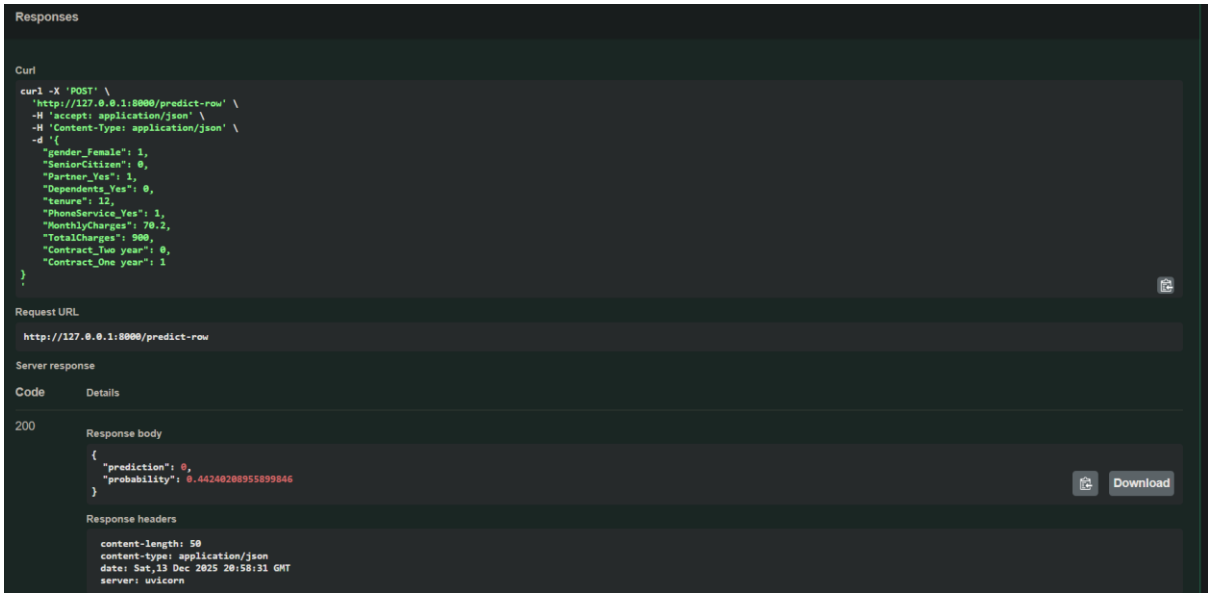
📌 Final Output with a Testcase:

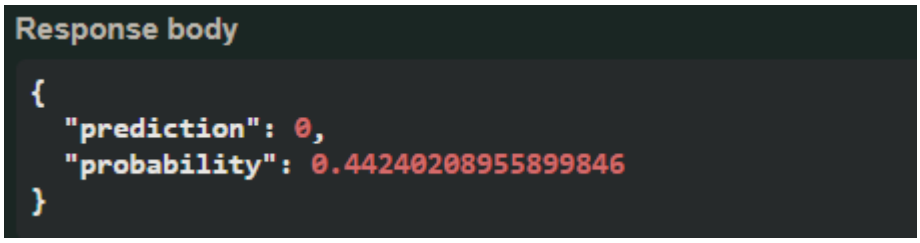
Testcase:

```
Sample Data to put in try out for swagger ui on the server:

{
    "gender_Female": 1,
    "SeniorCitizen": 0,
    "Partner_Yes": 1,
    "Dependents_Yes": 0,
    "tenure": 12,
    "PhoneService_Yes": 1,
    "MonthlyCharges": 70.2,
    "TotalCharges": 900,
    "Contract_Two year": 0,
    "Contract_One year": 1
}
```

Output:





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9. Conclusion

This project successfully demonstrates:

- A full machine learning workflow
- Proper preprocessing & encoding
- Handling class imbalance using SMOTE
- Training baseline & advanced ML models
- Evaluating using standard classification metrics
- Deploying the model as a working API

Random Forest achieved the best performance and was deployed via a scalable API, making this solution ready for real-world integration.