Bank Marketing Data Notebook

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The Project

This notebook documents the Data Science process for the **Tech Challenge 3** belonging to FIAP's Machine Learning Engineering PostGrad program.

In this project we will use the Bank Marketing dataset available at the UC Irvine Machine Learning Repository to build a model using **supervised learning techniques for classification tasks.**

Business Problem

A bank wants to improve the efficiency of its telemarketing campaigns for term deposits. Our goal is to create a machine learning model that can predict which clients are more likely to subscribe, allowing the bank to focus its efforts on the most promising leads, increasing the success rate and reducing marketing costs.

Methodology

This project follows a structured Machine Learning Workflow:

1. **Exploratory Data Analysis:** We will analyze the dataset to understand distributions, find patterns, and form our initial hypotheses.

   2.**Data Pipeline & Preprocessing:** We will build a simple classification model using *Logistic Regression* to build a baseline to compare our more complex models with. In this stage, we will also clean the data and engineer features based on insights from the exploratory analysis.

2. **Modeling & Comparison:** We will evaluate a suite of classifiers using cross-validation. Based on performance, we will select a few models for hyperparameter tuning with Optuna to extract the best performance possible.

3. **Conclusion:** In the conclusion, we will provide a final overview of our discoveries, models, and methodology, focusing on how this project can help with the solution of the business problem.

About the Dataset

The data is related to direct marketing campaigns of a Portuguese banking institution. These campaigns were primarily conducted via phone calls, and often, more than one contact to the same client was required to determine if the product (*a bank term deposit*) would be subscribed to.

The classification goal of this project is to predict if a client will subscribe (`yes` or `no`) to a term deposit, which is our target variable, `y` .

Inputs

To better understand the content of this dataset, we listed below the variable names, types, and description, as found in the variables table provided on the official UC Irvine Machine Learning Repository:

Variable Name	Type	Description
age	Integer	The person's age.
job	Categorical	Type of job (e.g., `admin`, `services`, etc.).
marital	Categorical	Marital status (e.g., `divorced`, `married`, etc.).
education	Categorical	Educational level (e.g., `high.school`, `university.degree`, etc.).
default	Binary	Has credit in default?
balance	Integer	Average yearly balance.
housing	Binary	Has housing loan?
loan	Binary	Has personal loan?
contact	Categorical	Contact communication type (e.g., `cellular`, `telephone`).
day_of_week	Date	Day of the week when the last contact was made.
month	Date	The month when the last contact was made.
duration	Integer	The duration, in seconds, of the last contact made.
campaign	Integer	Number of contacts performed during this campaing for this specific client, including the last contact.
pdays	Integer	Number of days that have passed by after the client was last contacted from a previous campaign (`-1` means client was **not** previously contacted).
previous	Integer	Number of contacts performed for this client before this campaign.
poutcome	Categorical	Outcome of the previous marketing campaign (`success`, `failure`, etc.)
y	Binary	**Target variable**. It answers if the client has subscribed to a term deposit.

In [43]:
```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.patches as mpatches
import time
import optuna
import joblib
```

```
import os
from sklearn.model_selection import train_test_split, StratifiedKFo
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, PowerTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import (RandomForestClassifier, GradientBoost
                              StackingClassifier, VotingClassifier,
from lightgbm import LGBMClassifier
from xgboost import XGBClassifier
from sklearn.metrics import (confusion_matrix, precision_score, rec
                             f1_score, roc_auc_score, RocCurveDispl
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
import warnings
warnings.filterwarnings('ignore')

# Settings and configurations
sns.set_style('whitegrid')
pd.set_option('display.max_columns', None)
```

In [44]:

```
# Defining seed for reproducibility
seed = 42
```

Exploratory Data Analysis

In this section, we'll conduct an EDA to understand the dataset. Our goal is to assess data quality, check missing values, and understand the relationship between features and the target variable. The insights gained here will be critical for guiding our feature engineering and modeling strategies in the next stages.

In [ ]:

```
# Defining functions for EDA
def display_feature_list(features, feature_type):
    '''
    This function displays the features within each list for each t
    '''

    print(f"\n{feature_type} Features: ")
    print(', '.join(features) if features else 'None')


def describe_df(df):
    """
    This function prints some basic info on the dataset and
    sets global variables for feature lists.
    """

    global categorical_features, continuous_features, binary_featur
    categorical_features = [
```

```
        col for col in df.columns if df[col].dtype == 'object']
    binary_features = [col for col in df.columns if df[col].nunique
    ) <= 2 and df[col].dtype != 'object']
    continuous_features = [
        col for col in df.columns if df[col].dtype != 'object' and

    print(f"\n{type(df).__name__} shape: {df.shape}")
    print(f"\n{df.shape[0]:,.0f} samples")
    print(f"\n{df.shape[1]:,.0f} attributes")
    display_feature_list(categorical_features, 'Categorical')
    display_feature_list(continuous_features, 'Continuous')
    display_feature_list(binary_features, 'Binary (0 or 1)')
    print(f'\nData Types: \n{df.dtypes}')
    print(
        f'\nMissing Data Percentage: \n{(df.isnull().sum() / len(df
    print(f'\nDuplicates: {df.duplicated().sum()}')
    print(
        f'\nCategorical Feature Cardinality: \n{df[categorical_feat
    print(
        f'\nFeatures with Zero Variance: {", ".join([col for col in

    negative_valued_features = [
        col for col in df[continuous_features] if (df[col] < 0).any
    print(
        f'\nFeatures with Negative Values: {", ".join(negative_valu

    print('\nStatistical Summary: \n')
    display(df.describe().T)
    print(f'\n{type(df).__name__} Head: \n')
    display(df.head(5))
    print(f'\n{type(df).__name__} Tail: \n')
    display(df.tail(5))
```

In [46]:

```
# Loading the dataset
df = pd.read_csv('../data/raw/bank_marketing.csv')
describe_df(df)
```

```
DataFrame shape: (45211, 17)

45,211 samples

17 attributes

Categorical Features:
job, marital, education, default, housing, loan, contact, month, pou
tcome, y

Continuous Features:
age, balance, day_of_week, duration, campaign, pdays, previous

Binary (0 or 1) Features:
None

Data Types:
age              int64
job             object
```

```
marital        object
education      object
default        object
balance         int64
housing        object
loan           object
contact        object
day_of_week     int64
month          object
duration        int64
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
dtype: object

Missing Data Percentage:
age              0.0%
job             0.64%
marital          0.0%
education       4.11%
default          0.0%
balance          0.0%
housing          0.0%
loan             0.0%
contact         28.8%
day_of_week      0.0%
month            0.0%
duration         0.0%
campaign         0.0%
pdays            0.0%
previous         0.0%
poutcome       81.75%
y                0.0%
dtype: object

Duplicates: 0

Categorical Feature Cardinality:
month        12
job          11
marital       3
education     3
poutcome      3
default       2
housing       2
loan          2
contact       2
y             2
dtype: int64

Features with Zero Variance: None

Features with Negative Values: balance, pdays
```

```
Statistical Summary:
```

	count	mean	std	min	25%	50%	75%
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.
day_of_week	45211.0	15.806419	8.322476	1.0	8.0	16.0	21.
duration	45211.0	258.163080	257.527812	0.0	103.0	180.0	319.
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.

```
DataFrame Head:
```

	age	job	marital	education	default	balance	housing	loan	con
0	58	management	married	tertiary	no	2143	yes	no	
1	44	technician	single	secondary	no	29	yes	no	
2	33	entrepreneur	married	secondary	no	2	yes	yes	
3	47	blue-collar	married	NaN	no	1506	yes	no	
4	33	NaN	single	NaN	no	1	no	no	

```
DataFrame Tail:
```

	age	job	marital	education	default	balance	housing	loa
45206	51	technician	married	tertiary	no	825	no	n
45207	71	retired	divorced	primary	no	1729	no	n
45208	72	retired	married	secondary	no	5715	no	n
45209	57	blue-collar	married	secondary	no	668	no	n
45210	37	entrepreneur	married	secondary	no	2971	no	n

- **Missing Data:** The dataset contains significant missing values that we must investigate further.
  - The `poutcome` feature is the most extreme case, with over 80% of its data missing.
  - The variables `contact`, `education`, and `job` also have a notable number of nulls that will require attention.
- **Feature Interpretation**
  - We have reasons to believe that the column `day_of_week` is mislabeled, given it ranges from 1 to 31, signaling it refers to the day

of the month, instead of day of the week.
  - We can see that many numerical features, such as `balance`, `campaign`, and `duration`, are heavily right-skewed, indicating that transformations will be necessary before feeding them to our baseline model. That's because linear models, like Logistic Regression, are very sensitive to the scale of the data and can become biased towards values that are far away from the rest of the data.
- **Data Leakage**
  - Feature `duration` represents a data leak. Its value is *unknown* before a call is made, so it must be dropped from our dataset before building our models.

Categorical Features

Our data has a set of both categorical and continuous features. Let's first focus on the categorical features. We will start by analyzing the distribution of the target variable `y` and then see how the subscription rate varies across different categories.

In [ ]:
```
# EDA Plots
def plot_stacked_bar_percentage(df, feat, target, positive_class='y
    """
    This function plots a 100% stacked bar chart to show the relati
    between a categorical feature and a binary target variable, inc
    Bars are sorted by the percentage of the positive class.
    """
    palette = ['#29788E', '#E85B5B']

    feature_data = df[feat].fillna('Missing')

    ct = pd.crosstab(feature_data, df[target], normalize='index')

    ct = ct.sort_values(by=positive_class, ascending=False)

    ax = ct.plot(
        kind='barh',
        stacked=True,
        color=palette,
        figsize=(12, 8),
        legend=False
    )

    fig = ax.get_figure()
    fig.set_facecolor('#f5f7f6')
    ax.set_facecolor('#f5f7f6')
    ax.tick_params(axis='x', colors='#555555')
    ax.tick_params(axis='y', colors='#555555')

    for p in ax.patches:
```

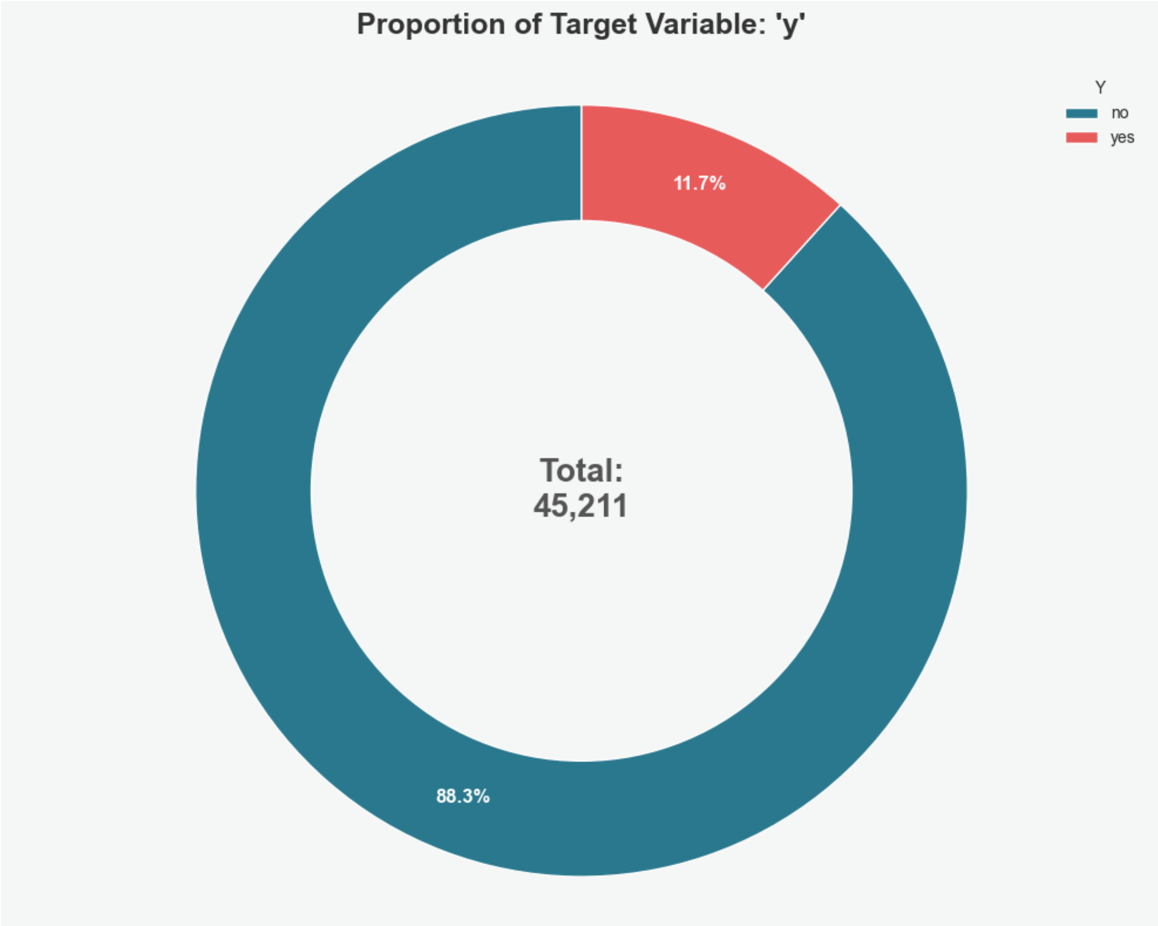
```
        width = p.get_width()
        height = p.get_height()
        x, y = p.get_xy()
        if width > 0:
            ax.text(
                x + width / 2,
                y + height / 2,
                f'{width:.1%}',
                ha='center',
                va='center',
                color='white',
                fontsize=12,
                fontweight='bold'
            )

    ax.set_title(
        f"Proportion of '{target}' by '{feat}'",
        fontsize=18, fontweight='bold', pad=20, loc='left', color='
    )
    ax.set_xlabel(
        'Proportion', fontweight='bold', color='#555555'
    )
    ax.set_ylabel(
        feat.title(), fontweight='bold', color='#555555'
    )

    ax.legend(
        title=target.title(),
        bbox_to_anchor=(1.02, 1),
        loc='upper left',
    )

    ax.xaxis.set_major_formatter(plt.FuncFormatter('{:.0%}'.format)
    ax.invert_yaxis()

    sns.despine(left=True, bottom=True)
    plt.tight_layout()
    plt.show()
```

In [ ]:

```
# EDA Plots
def plot_donut(df, feat):
    """
    This function plots a donut chart to show the distribution of a
    """
    counts = df[feat].value_counts()
    labels = counts.index
    values = counts.values

    palette = {
        'no': '#29788E',
        'yes': '#E85B5B'
    }
    colors = [palette.get(label, '#CCCCCC') for label in labels]

    plt.style.use('seaborn-v0_8-whitegrid')
    fig, ax = plt.subplots(figsize=(10,8))
```

```
    fig.set_facecolor('#f5f7f6')

    wedges, texts, autotexts = ax.pie(
        values,
        autopct='%1.1f%%',
        startangle=90,
        colors=colors,
        pctdistance=0.85,
        textprops={'fontsize': 12, 'fontweight': 'bold', 'color': '
    )

    center_circle = plt.Circle((0,0),0.70,fc='#f5f7f6')
    ax.add_artist(center_circle)

    total = df[feat].count()
    ax.text(
        0,0,
        f'Total:\n{total:,}',
        ha='center',
        va='center',
        fontsize=20,
        fontweight='bold',
        color='#555555'
    )

    ax.set_title(
        f"Proportion of Target Variable: '{feat}'",
        fontsize=18, fontweight='bold', pad=20, loc='center', color
    )

    ax.axis('equal')

    ax.legend(
        wedges,
        labels,
        title=feat.title(),
        loc='upper right'
    )
    plt.tight_layout()
    plt.show()
```

In [49]:
```
# Obtaining the proportion of labels in the target variable
plot_donut(df, 'y')
```

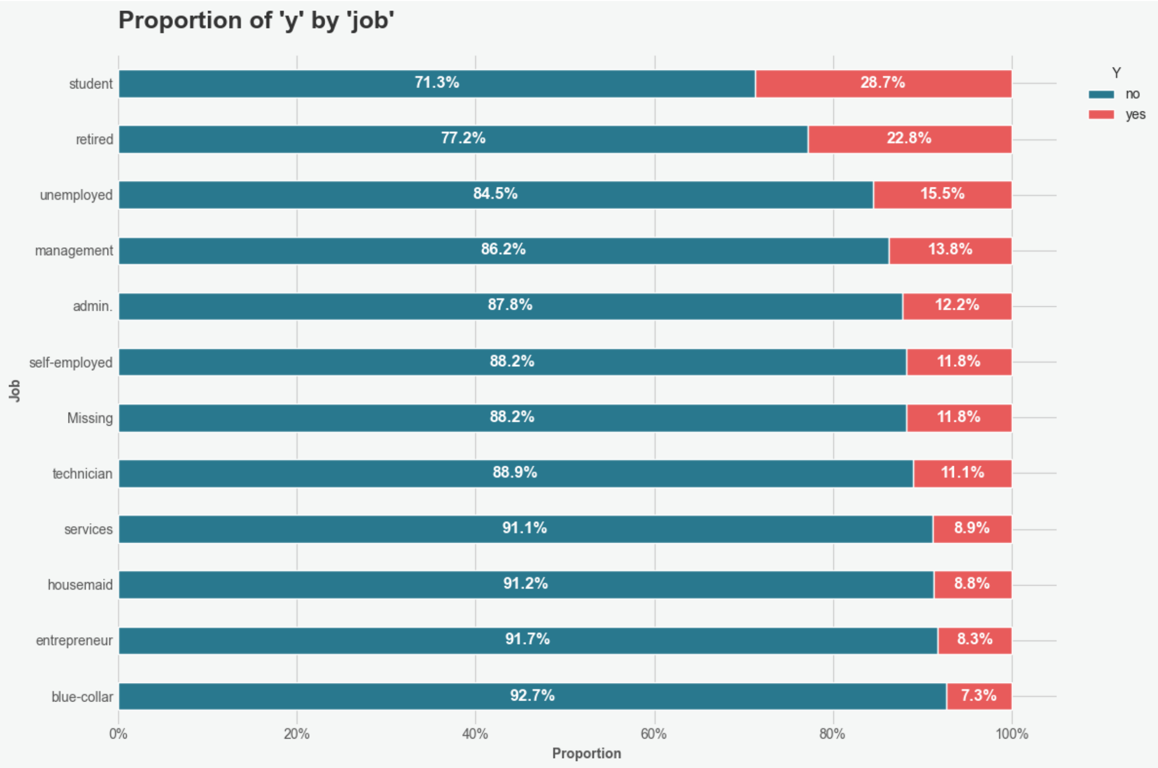


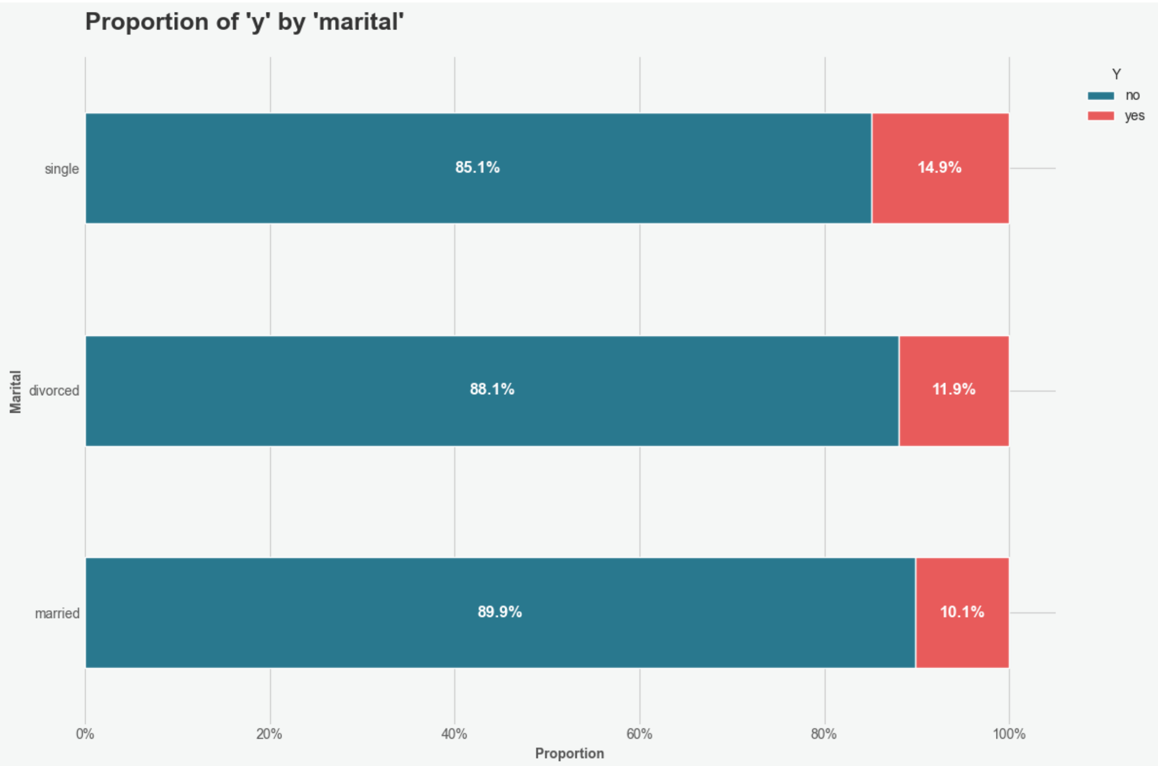
- **Class Distribution**
  - The chart above shows that our dataset is **highly imbalanced**, meaning that both classes are **not** represented equally. The negative class `no` is the overwhelming majority, accounting for 88.3% (39,922 instances) of a total of 45,211 samples. The `yes` class, on the other hand, accounts for a small minority of 5,289 instances (11.7% of the total).

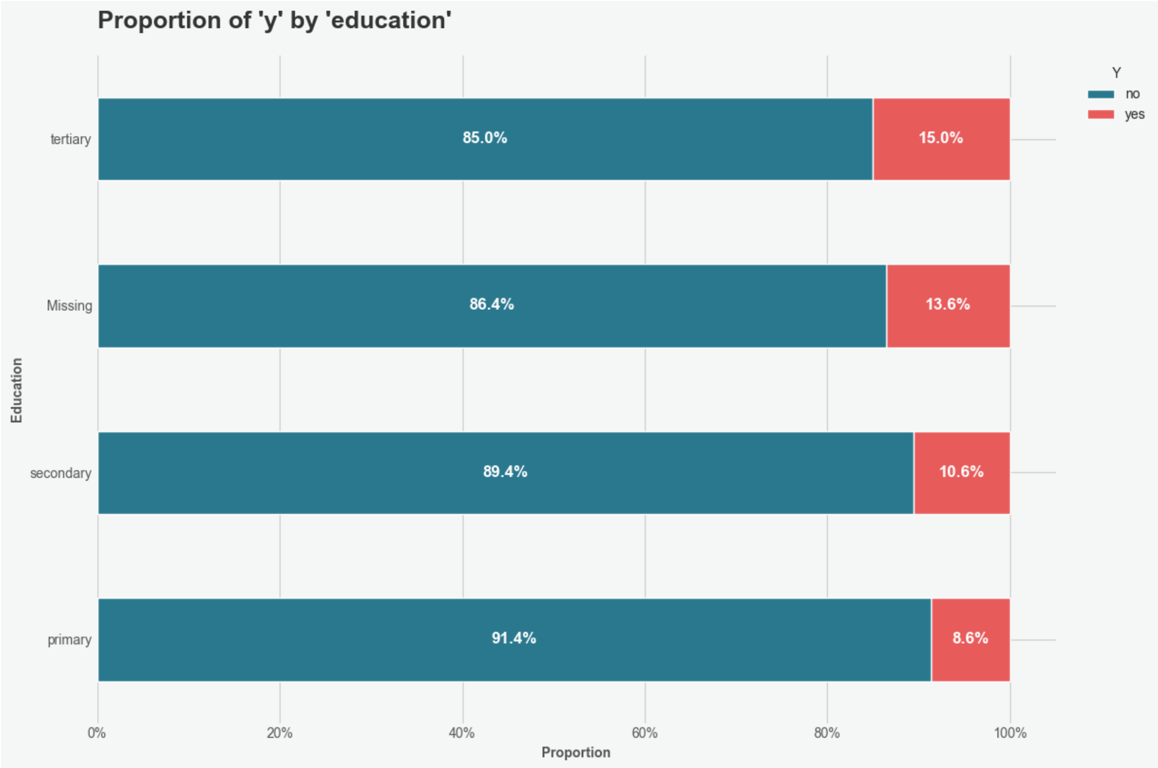
  - Given this context, a lazy model could achieve 88.3% accuracy by simply predicting *'no'* every single time. `Accuracy` will be a misleading metric.

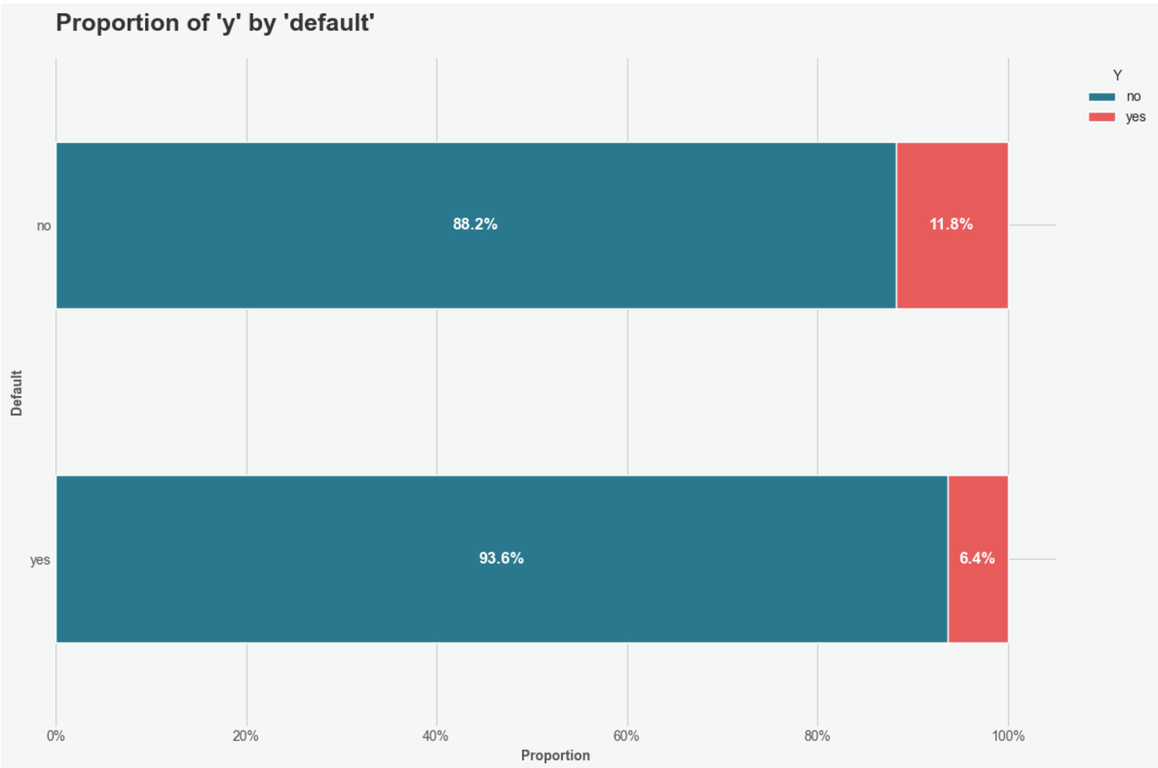
- **Dealing with Imblanced Labels**
  - Considering the class imbalance, we must focus on other metrics besides accuracy. We must also use the right strategy to deal with imbalance, such as defining the `class_weight='balanced'` param in our models or use techniques like SMOTE to oversample the minority class.

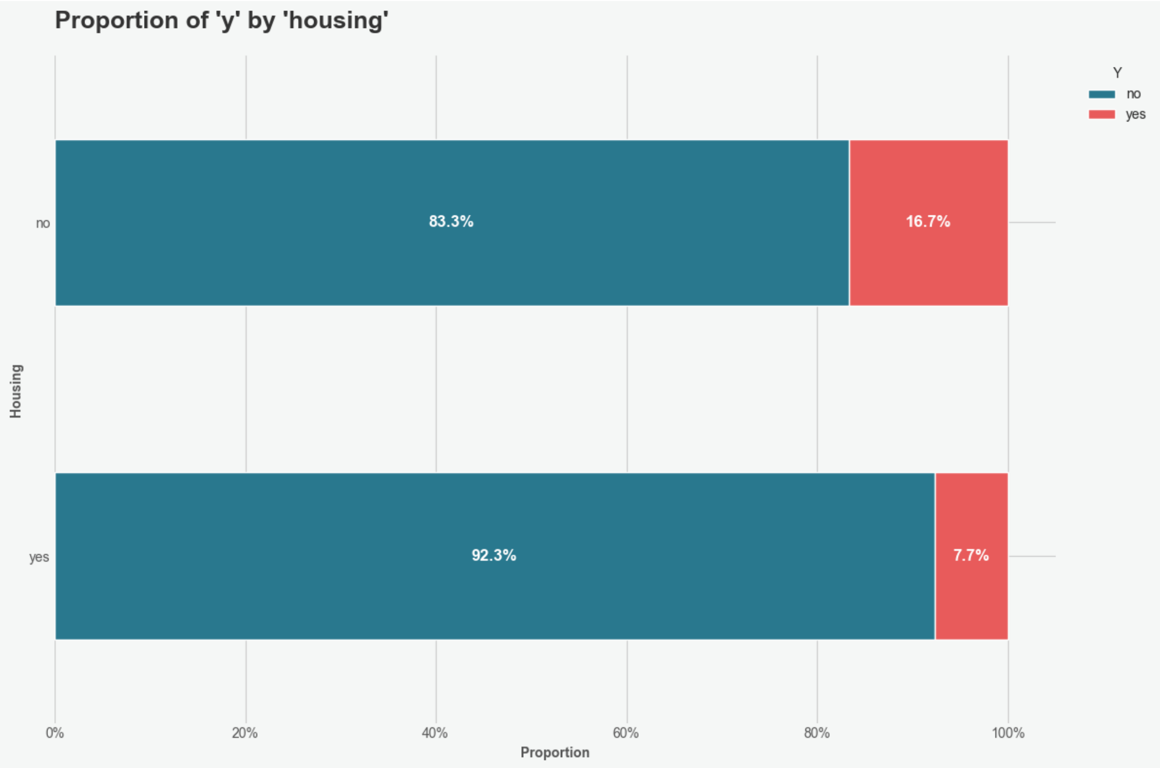
In [50]:
```
# Observing the relationship between categorical features and the t
categorical_features.remove('y')
for feat in df[categorical_features]:
    plot_stacked_bar_percentage(df, feat, 'y')
```

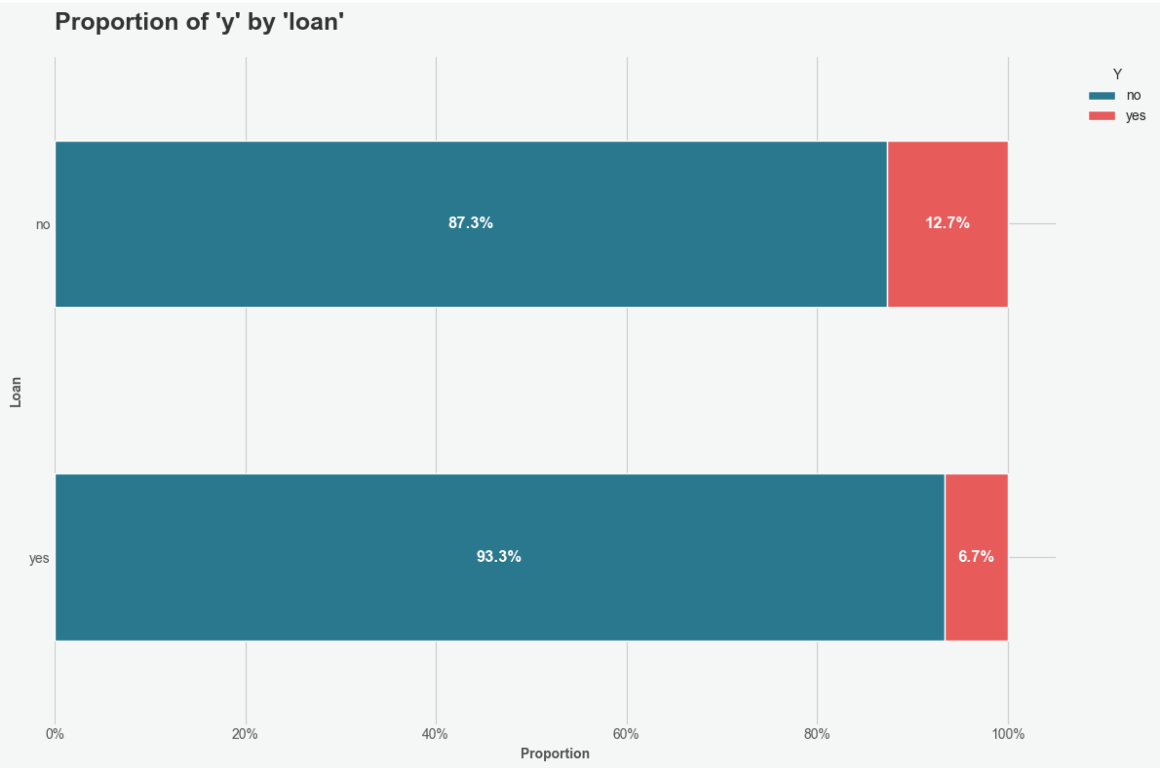

Proportion of 'y' by 'job'
Y
no
yes
student 71.3% 28.7%
retired 77.2% 22.8%
unemployed 84.5% 15.5%
management 86.2% 13.8%
admin. 87.8% 12.2%
self-employed 88.2% 11.8%
Missing 88.2% 11.8%
technician 88.9% 11.1%
services 91.1% 8.9%
housemaid 91.2% 8.8%
entrepreneur 91.7% 8.3%
blue-collar 92.7% 7.3%
Job
0% 20% 40% 60% 80% 100%
Proportion

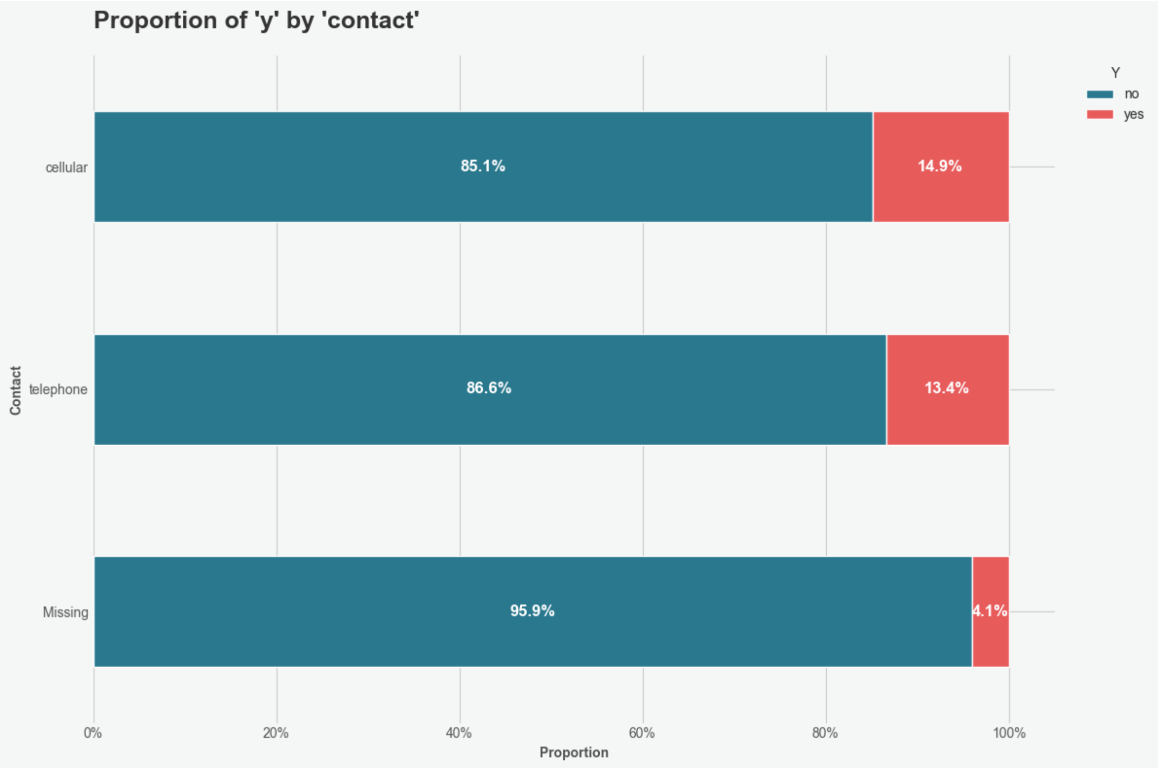

Proportion of 'y' by 'marital'
Y
no
yes
single 85.1% 14.9%
divorced 88.1% 11.9%
married 89.9% 10.1%
Marital
0% 20% 40% 60% 80% 100%
Proportion

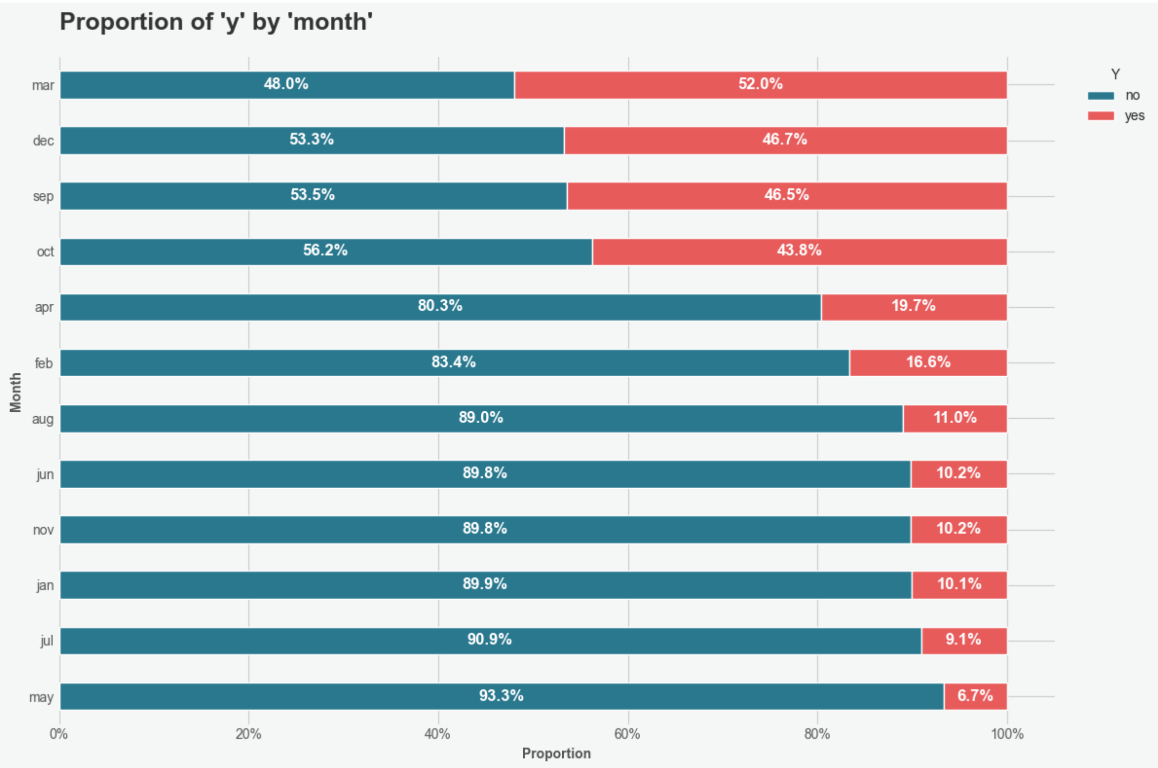

Proportion of 'y' by 'education'
Y
no
yes
tertiary
Missing
secondary
primary
Education
85.0%
15.0%
86.4%
13.6%
89.4%
10.6%
91.4%
8.6%
0%
20%
40%
60%
80%
100%
Proportion

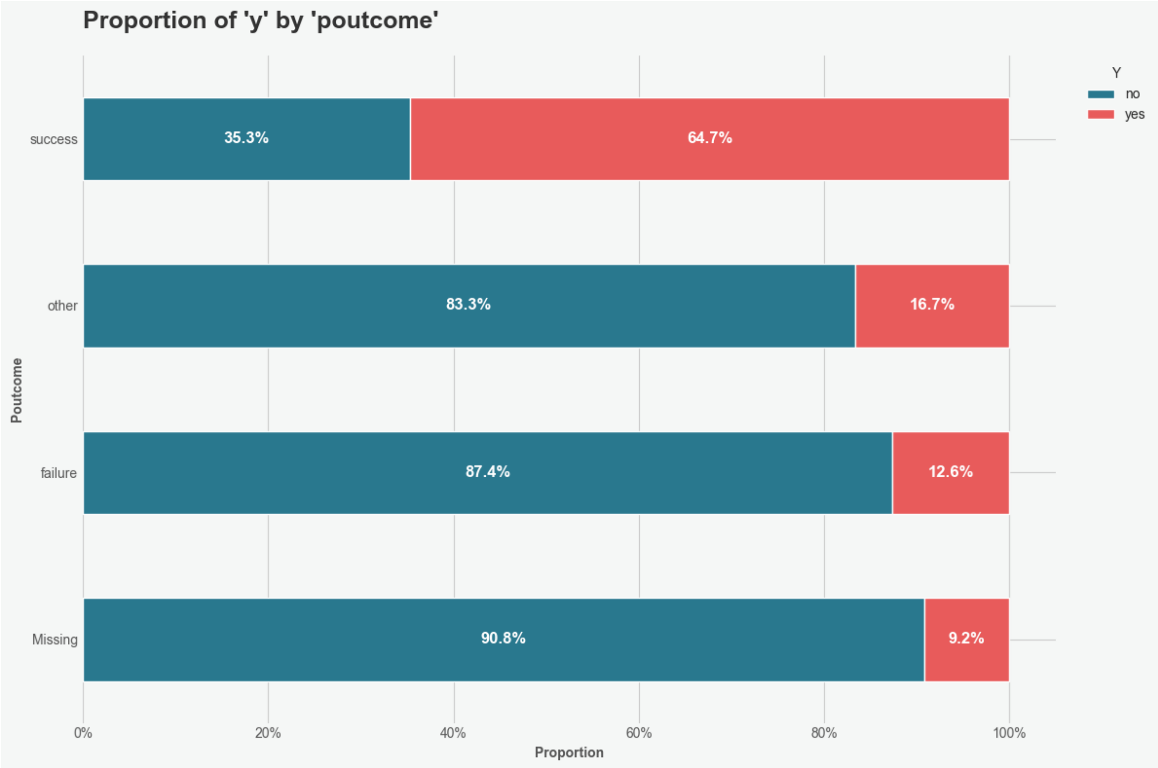

Proportion of 'y' by 'default'
Y
no
yes
no
yes
Default
88.2%
11.8%
93.6%
6.4%
0%
20%
40%
60%
80%
100%
Proportion


Proportion of 'y' by 'housing'
Y
no
yes
no
83.3%
16.7%
yes
92.3%
7.7%
Housing
0%
20%
40%
60%
80%
100%
Proportion


Proportion of 'y' by 'loan'
Y
no
yes
no
87.3%
12.7%
yes
93.3%
6.7%
Loan
0%
20%
40%
60%
80%
100%
Proportion


Proportion of 'y' by 'contact'
Y
no
yes
cellular
85.1%
14.9%
telephone
86.6%
13.4%
Missing
95.9%
4.1%
Contact
0%
20%
40%
60%
80%
100%
Proportion


Proportion of 'y' by 'month'
Y
no
yes
mar 48.0% 52.0%
dec 53.3% 46.7%
sep 53.5% 46.5%
oct 56.2% 43.8%
apr 80.3% 19.7%
feb 83.4% 16.6%
aug 89.0% 11.0%
jun 89.8% 10.2%
nov 89.8% 10.2%
jan 89.9% 10.1%
jul 90.9% 9.1%
may 93.3% 6.7%
Month
0%
20%
40%
60%
80%
100%
Proportion



- **Time-Based & Behavioral Features**
  - The `month` variable appears to be a good predictor. There is a clear seasonal pattern, where campaings in March, September, October and December are wildly successful. May and July, on the other hand, presented worse outcomes.

  - The previous campaign outcome (`poutcome`) is also a powerful indicator. Clients with a prior '*success*' are more likely to subscribe again.
- **Demographics & Occupation**
  - The `job` type reveals interesting patterns as well. Those labeled as `student` and `retired` appears to have the highest propensity to subscribe. On the other hand, `blue-collar` workers and `entrepreneur` were the least likely.

  - A similar trend can be observed for `marital` status and `education` . `Single` clients and those with `tertiary` (i.e., higher education) had slightly higher success rates.
- **Financial Status**
  - Binary categorical features (`housing` , `loan` , and `default`) also show interesting insights. Subscriptions are more common proportionally among those with no existing housing loan, no personal loan, and no credit default. This could indicate that clients with fewer financial liabilities are a more receptive audience for this product.

Continuous Features

Now we'll turn our attention to the continuous features. We will analyze their distributions and explore how they relate to the subscription outcome. We will also use a correlation matrix to assess any relationships between the numerical features themselves.

In [ ]:
```
# EDA Plots
def plot_hist_box(df, feat):
    """
    This function plots a histogram and a box plot side-by-side
    for a given continuous feature.
    """
    fig, axes = plt.subplots(
        1,2,
        figsize=(14, 6),
        facecolor='#f5f7f6',
        gridspec_kw={'width_ratios': [1, 4]}
    )

    fig.suptitle(
        f'Distribution of {feat}',
        fontsize=18, fontweight='bold', color='#333333', y=1.05
    )
    sns.boxplot(
        y=df[feat],
        ax=axes[0],
        color='#D32F2F',
        boxprops=dict(alpha=.7),
        medianprops=dict(color='white', linewidth=2)
    )
    axes[0].set_facecolor('#f5f7f6')
    axes[0].set_title('Box Plot', fontsize=14, fontweight='bold', c
    axes[0].set_ylabel(feat.title(), fontweight='bold', color='#555
    axes[0].set_xlabel('')

    sns.histplot(
        data=df,
        x=feat,
        ax=axes[1],
        color='#1976D2',
        kde=True,
        alpha=0.6,
        edgecolor='w',
        linewidth=1.5
    )
    axes[1].set_facecolor('#f5f7f6')
    axes[1].set_title('Histogram & Density Curve (KDE)', fontsize=1
    axes[1].set_xlabel(feat.title(), fontweight='bold', color='#555
    axes[1].set_ylabel('Frequency', fontweight='bold', color='#5555

    sns.despine(left=True, bottom=True)
    plt.tight_layout(rect=[0,0,1,0.96])
```

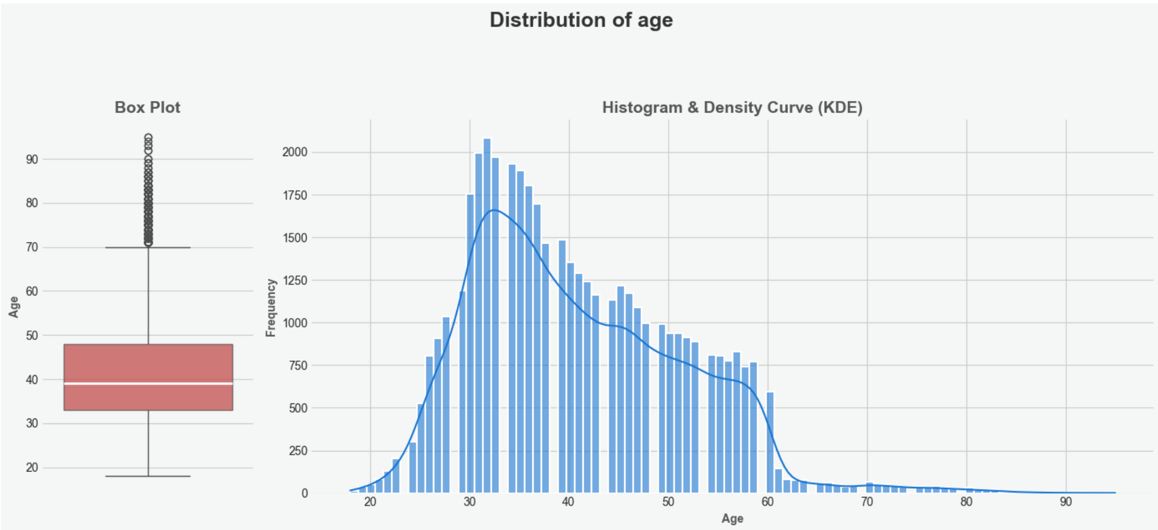
```
    plt.show()
```

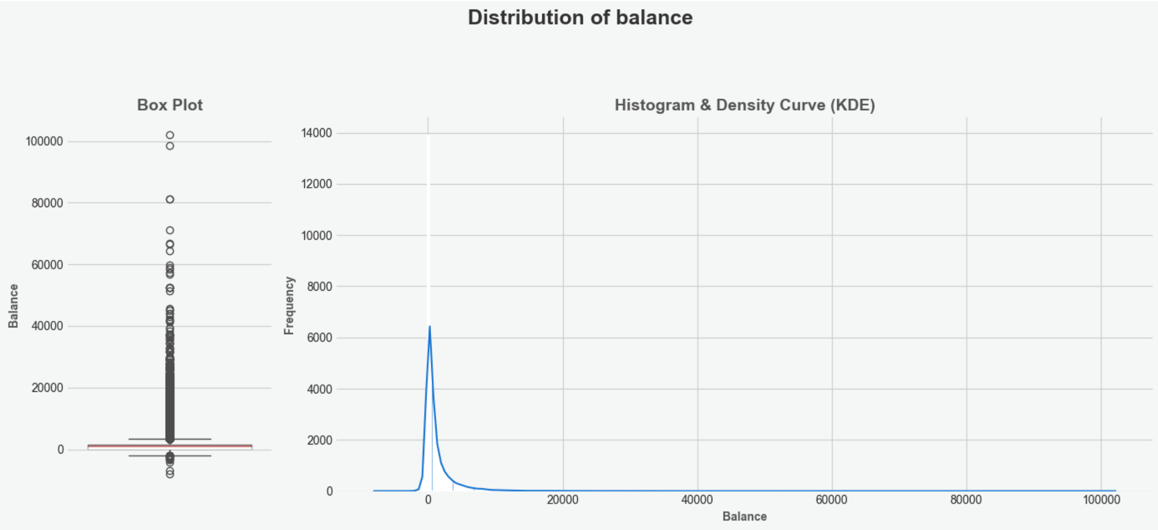
In [ ]:
```
# EDA plots
def plot_kde_by_target(df, cont_feat, target):
    """
    This function plots overlapping KDEs for a continuous feature,
    separated by the binary target variable.
    """
    palette = {
        'no': '#29788E',
        'yes': '#E85B5B'
    }

    plt.style.use('seaborn-v0_8-whitegrid')
    fig, ax = plt.subplots(figsize=(12, 7))
    fig.set_facecolor('#f5f7f6')
    ax.set_facecolor('#f5f7f6')

    sns.kdeplot(
        data=df,
        x=cont_feat,
        hue=target,
        fill=True,
        common_norm=False,
        alpha=0.6,
        palette=palette,
        linewidth=2.5,
        ax=ax
    )

    ax.set_title(
        f"Distribution of '{cont_feat}' by '{target}'",
        fontsize=18, fontweight='bold', pad=20, loc='left', color='
    )

    ax.set_xlabel(
        cont_feat.title(), fontweight='bold', color='#555555'
    )
    ax.set_ylabel(
        'Density', fontweight='bold', color='#555555'
    )

    sns.despine(left=True, bottom=True)
    plt.tight_layout()
    plt.show()
```

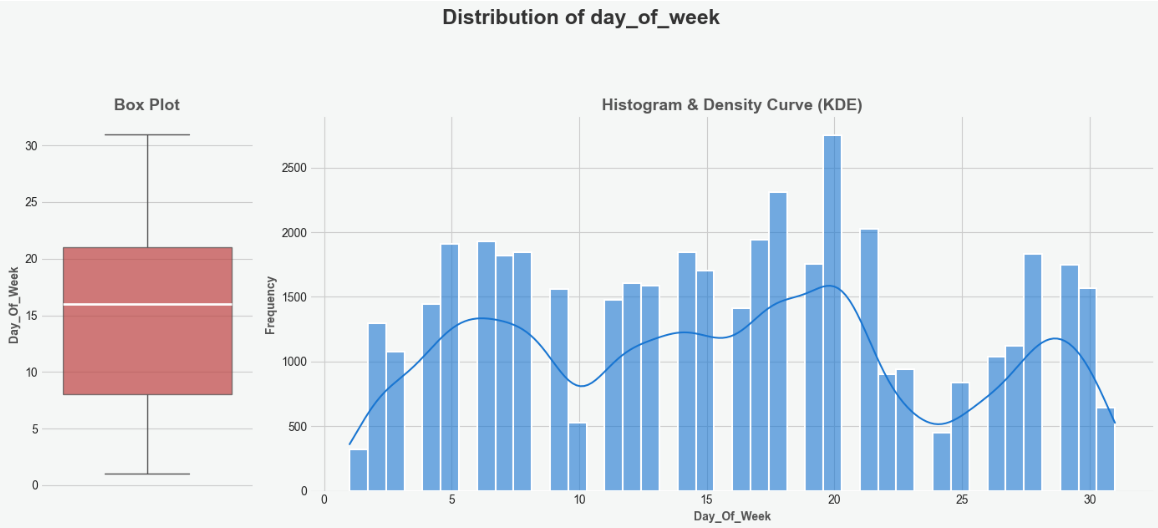
In [ ]:
```
# EDA Plots
def plot_correlation_heatmap(df):
    """
    This function plots a correlation heatmap for numerical feature
    """

    corr = df.corr(numeric_only=True).round(2)

    mask = np.triu(np.ones_like(corr, dtype=bool))
```

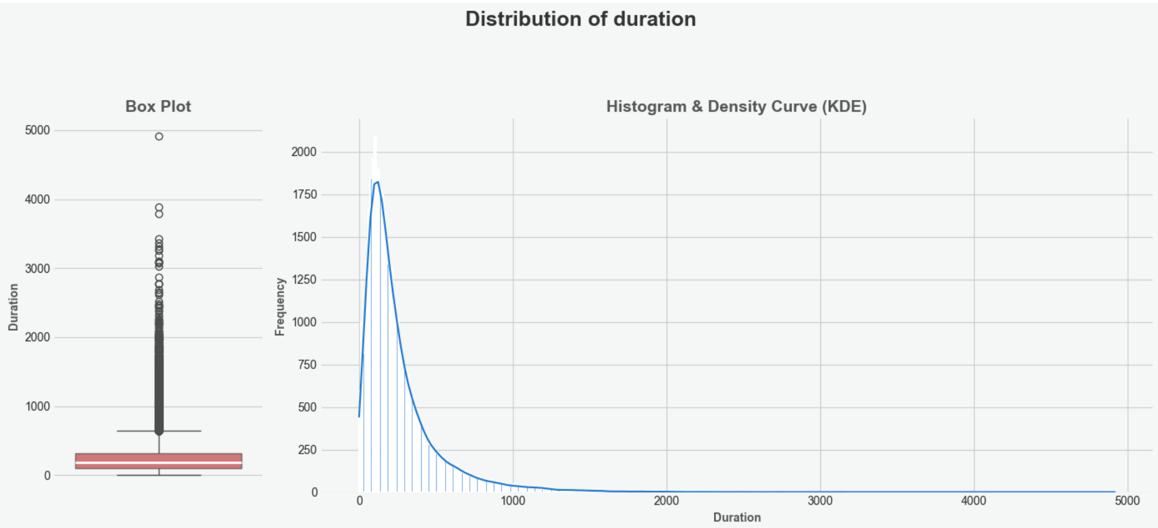
```
    fig, ax = plt.subplots(figsize=(10, 8))
    fig.set_facecolor('#f5f7f6')

    sns.heatmap(
        corr,
        mask=mask,
        annot=True,
        fmt='.2f',
        cmap='YlOrBr',
        center=0,
        square=True,
        linewidths=.5,
        cbar_kws={"shrink": .8},
        ax=ax
    )

    ax.set_title(
        'Feature Correlation Heatmap',
        fontsize=18, fontweight='bold', pad=20, loc='left', color='
    )
    plt.xticks(rotation=45, ha='right', fontsize=10, color='#555555
    plt.yticks(rotation=0, fontsize=10, color='#555555')

    plt.tight_layout()
    plt.show()
```

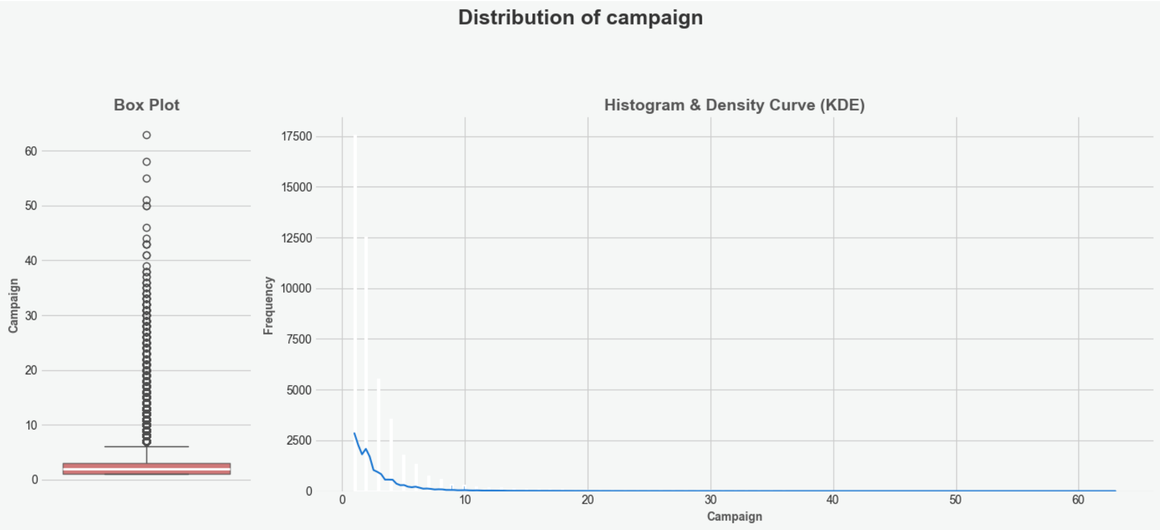
In [ ]:
```
# Plotting Box Plot and Histogram for continuous features
for feat in continuous_features:
    plot_hist_box(df, feat)
```

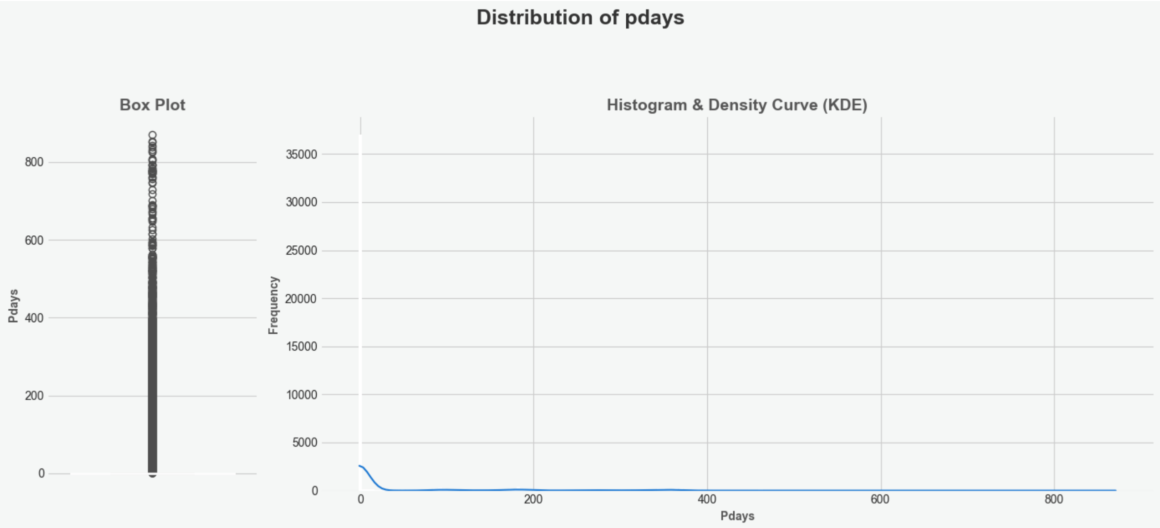


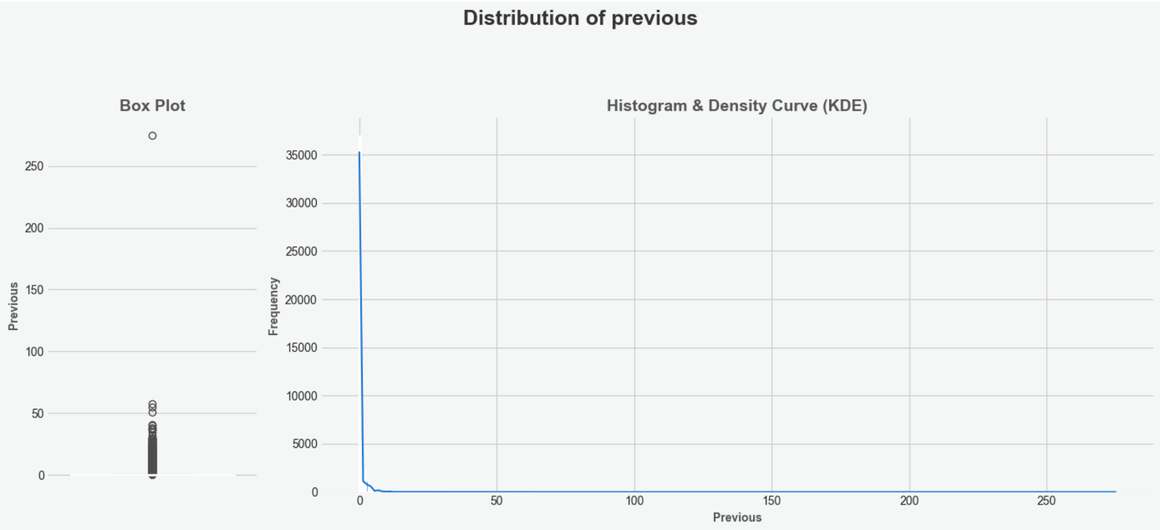

Distribution of balance
Box Plot
Balance
100000
80000
60000
40000
20000
0
Histogram & Density Curve (KDE)
Frequency
14000
12000
10000
8000
6000
4000
2000
0
20000
40000
60000
80000
100000
Balance


Distribution of day_of_week
Box Plot
Day_Of_Week
30
25
20
15
10
5
0
Histogram & Density Curve (KDE)
Frequency
2500
2000
1500
1000
500
0
5
10
15
20
25
30
Day_Of_Week


Distribution of duration
Box Plot
Duration
5000
4000
3000
2000
1000
0
Histogram & Density Curve (KDE)
Frequency
2000
1750
1500
1250
1000
750
500
250
0
1000
2000
3000
4000
5000
Duration



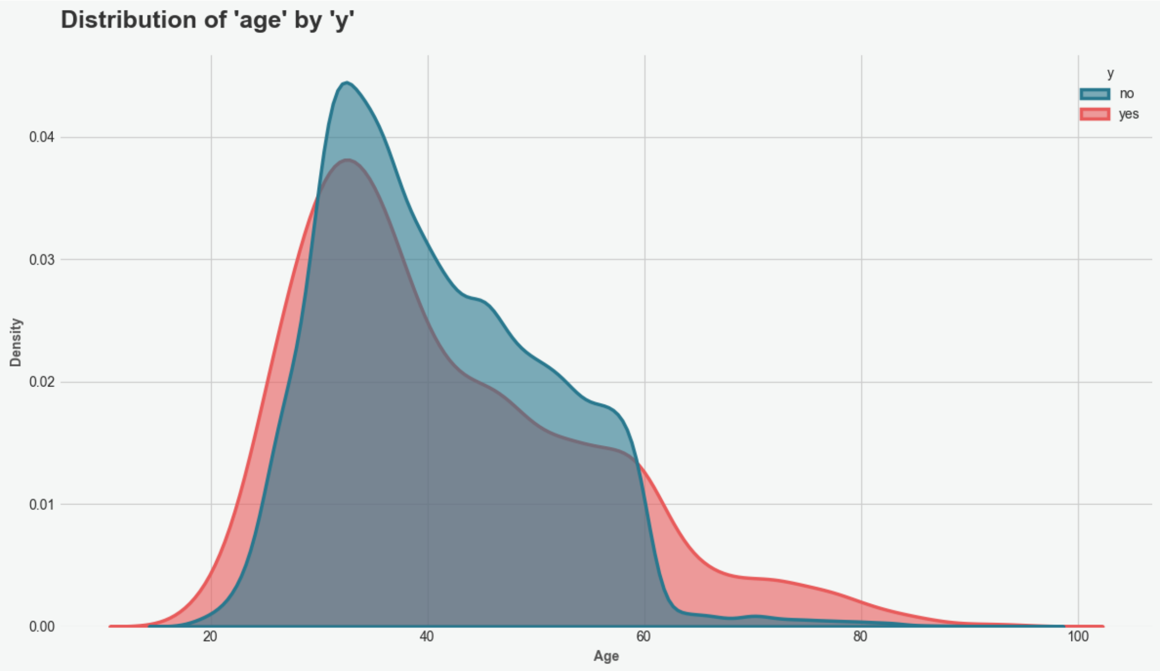


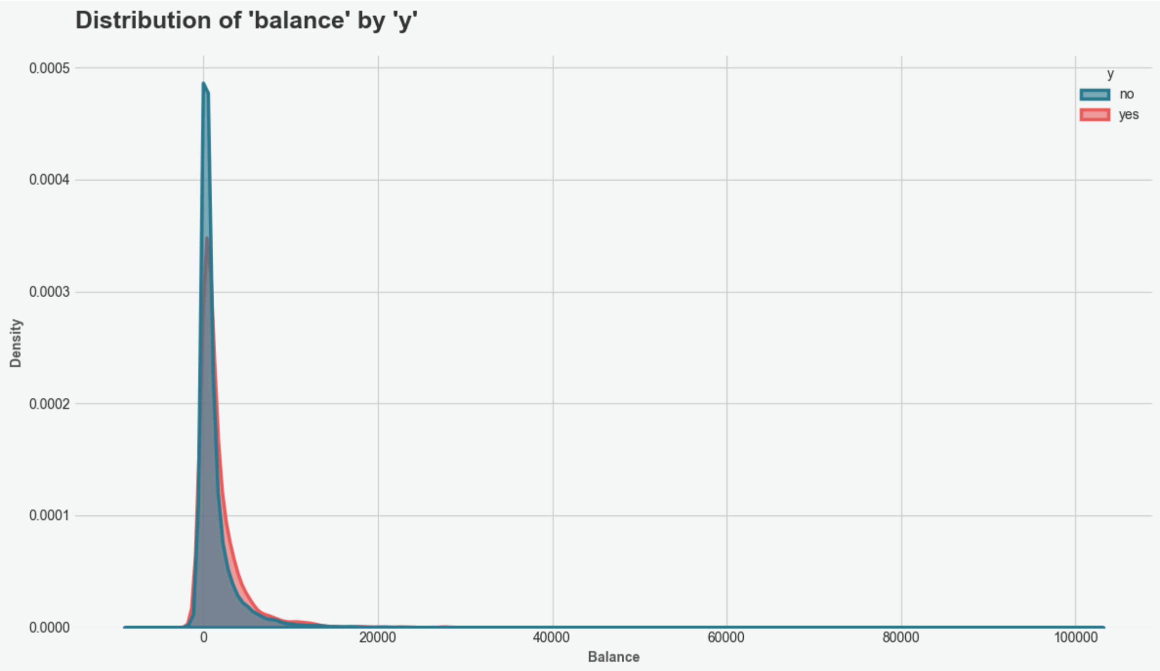


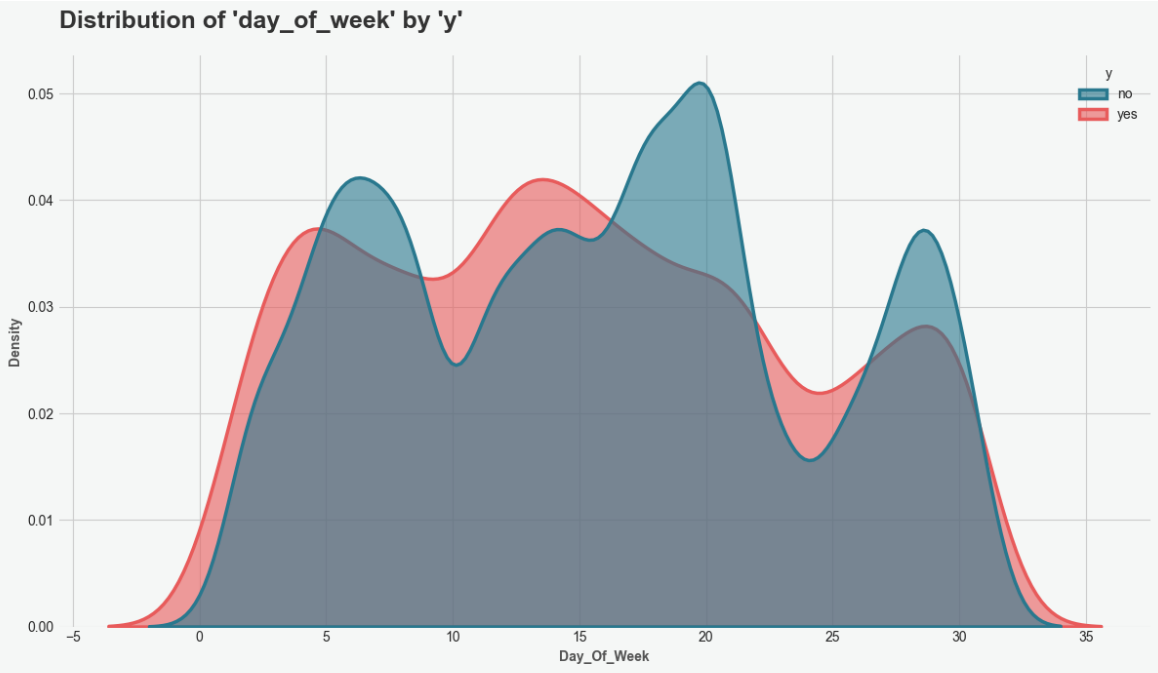
- **Skewness**
  - The variables `balance`, `duration`, and `campaign` are heavily right-skewed. That means there is a much larger concentration of data points at the lower end with a long tail of extreme, but less frequent, values. For **linear models** (e.g., Support Vector Machines, Logistic Regression) and **distance-based** algorithms (e.g., KMeans), this skew can be problematic.

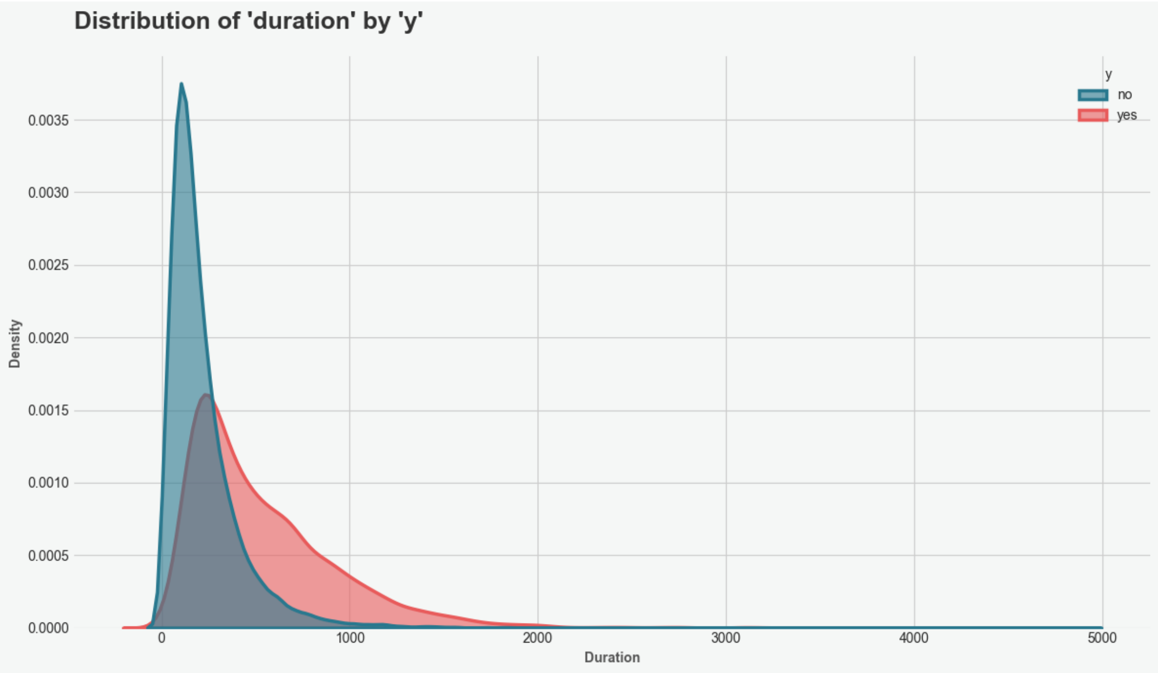
- **Quasi-Categorical Features**
  - The `pdays` and `previous` features are not truly continuous but behave as *quasi-categorical variables*. Each is dominated by a single value (-1 for `pdays` and 0 for `previous`), which accounts for over 80% of the data. This indicates they should be re-engineered into binary or categorical features rather than being treated as numerical.

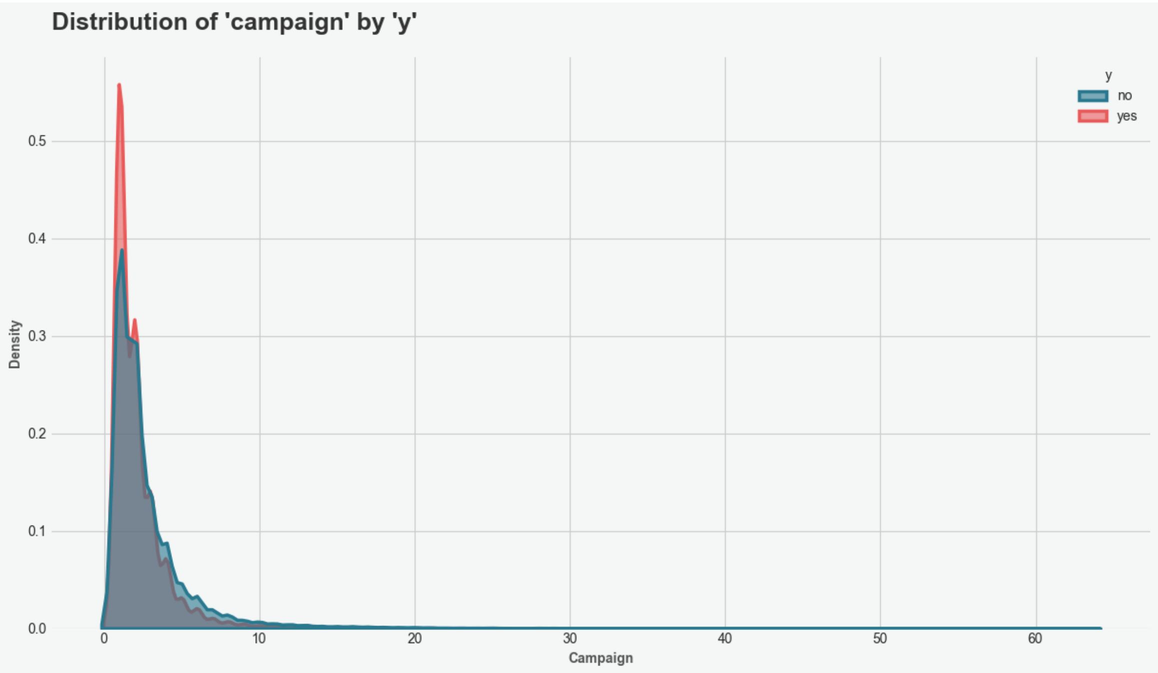
In [ ]:
```python
# Plotting KDE plots for continuous features by target variable
for feat in continuous_features:
    plot_kde_by_target(df, feat, 'y')
```

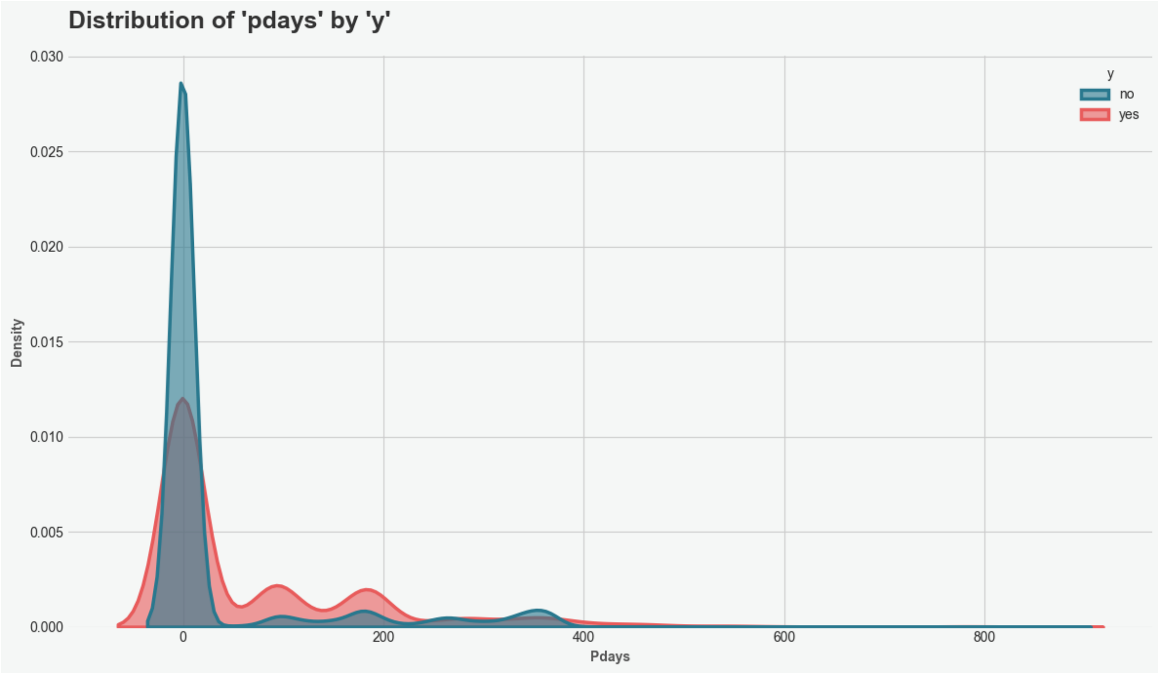


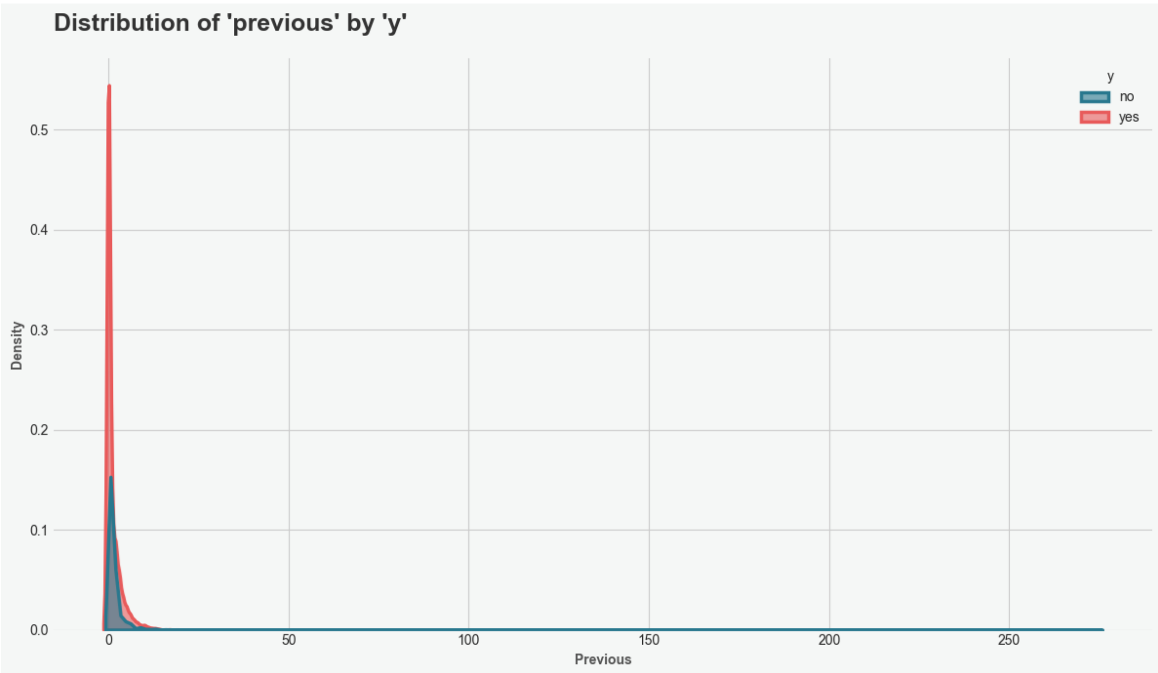



Distribution of 'day_of_week' by 'y'
Density
Day_Of_Week
y
no
yes
0.00
0.01
0.02
0.03
0.04
0.05
−5
0
5
10
15
20
25
30
35


Distribution of 'duration' by 'y'
Density
Duration
y
no
yes
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0
1000
2000
3000
4000
5000


Distribution of 'campaign' by 'y'
Density
Campaign
y
no
yes
0.0
0.1
0.2
0.3
0.4
0.5
0
10
20
30
40
50
60



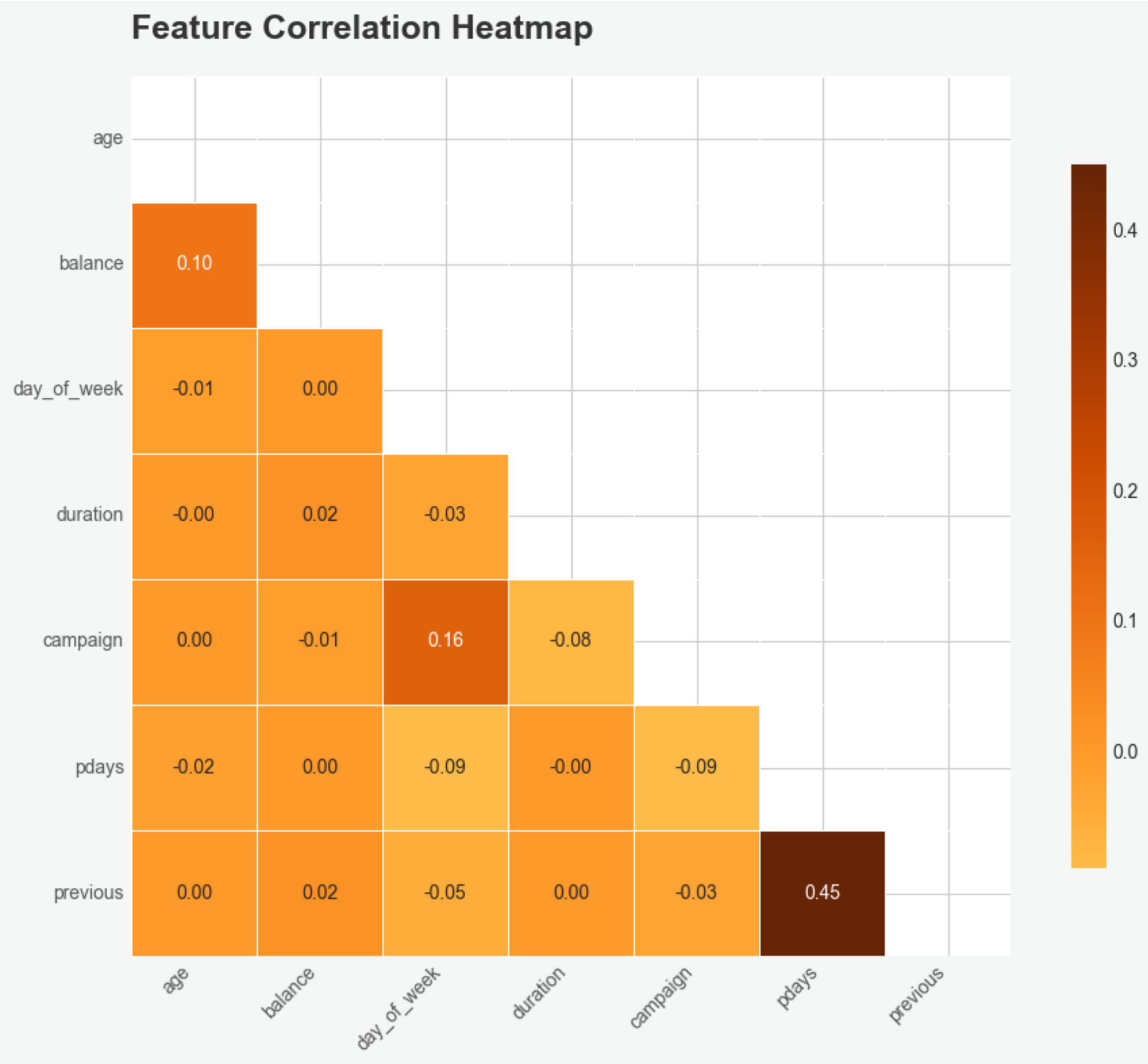


- **Data Leakage**
  - The `duration` of the call is highly correlated with the outcome, with longer calls strongly indicating a subscription. However, we known this is a data leak, since the duration is only known *after* the call is made. We will remove this feature from the dataset before modeling.
- **Behavioral Predictors**
  - The number of contacts (`campaign`) appears to be a relevant predictor. Successful outcomes are heavily concentrated in the **first one or two contacts**. The data clearly shows that repeated contacts lead to diminishing returns, with a high number of calls being strongly associated with a negative outcome.

- Similarly, prior engagement (`pdays`) is a positive signal. While most clients have never been contacted before (`pdays = -1`), those who *have* been previously contacted show a higher propensity to subscribe.

- **Demographic Insights**
  - The `age` distribution confirms our findings from the `job` analysis. There is a higher likelihood of subscription among clients at the extremes of the age range: **younger clients (typically students)** and **older clients (typically retired)**.

In [ ]:
```
# Plotting correlation heatmap
plot_correlation_heatmap(df)
```



- **Moderate Positive Correlation**
  - The most significant correlation is a moderate positive relationship between `pdays` and `previous` . This is expected, because both features are related to past contact history. If a client has had previous contact (`previous` > 0), then pdays will also have a value

other than `-1`. They are measuring a similar underlying concept.

- **Absence of Linear Trends**
  - Overall, the correlation heatmap shows that there are no linear trends among continuous features (e.g., *"as age increases, balance increases*). This lack of strong linear relationships suggest that linear models might struggle to find patterns without a significant level of feature engineering. Non-linear models, like Random Forest or Gradient Boosting, might be able to capture more complex relationships between features.

Data Pipeline & Preprocessing

In this section, we will start by building a baseline. We will then perform some feature engineering based on our findings and build the data pipeline that will be used to automate and encapsulate all our preprocessing workflow.

Baseline

Let's start by building a baseline with a simple Logistic Regression model to evaluate performance.

During our EDA, we uncovered that `poutcome` feature has over 80% of missing data. Our first inclination was to drop this feature, due to a high number of missing data. However, given that this feature appears to have important predictive power (64.7% of clients whose previous marketing campaign was a `success` said `yes` to this current campaign), we might want to test performance of a baseline model **with and without** this feature.

If including `poutcome` gives us a signifcant performance boost, we will know it is worth it to keep this feature. However, if performance is worse, we will opt for excluding it.

In [57]:
```
# Creating a copy of the original dataframe for preprocessing and m
df_model = df.copy()

# Dropping the 'duration' feature due to data leakage
df_model.drop(columns=['duration'], axis=1, inplace=True)

# Filling missing values in categorical features with 'Unknown'
df_model[categorical_features] = df_model[categorical_features].fil
```

```
# Separating features and target variable
X = df_model.drop('y', axis=1)
y = df_model['y'].map({'yes': 1, 'no': 0}) # Encoding target variab

print("--- Features and Target Variable ---")
print("\nFeatures:\n")
print(X.shape)
print('\n')
print(X.head())
print("\nTarget Variable:\n")
print(y.shape)
print('\n')
print(y.head())
print("\n------------------------------------\n")
print("Missing Data Check:\n")
print(df_model.isnull().sum())
print("\n------------------------------------\n")
```

```
--- Features and Target Variable ---

Features:

(45211, 15)


   age           job  marital  education default  balance housing lo
an  \
0   58    management  married   tertiary      no     2143     yes   
no   
1   44    technician   single  secondary      no       29     yes   
no   
2   33  entrepreneur  married  secondary      no        2     yes   y
es   
3   47   blue-collar  married    unknown      no     1506     yes   
no   
4   33       unknown   single    unknown      no        1      no   
no   

   contact  day_of_week month  campaign  pdays  previous poutcome  
0  unknown            5   may         1     -1         0  unknown  
1  unknown            5   may         1     -1         0  unknown  
2  unknown            5   may         1     -1         0  unknown  
3  unknown            5   may         1     -1         0  unknown  
4  unknown            5   may         1     -1         0  unknown  

Target Variable:

(45211,)


0    0
1    0
2    0
3    0
4    0
Name: y, dtype: int64
```

```
------------------------------------

Missing Data Check:

age            0
job            0
marital        0
education      0
default        0
balance        0
housing        0
loan           0
contact        0
day_of_week    0
month          0
campaign       0
pdays          0
previous       0
poutcome       0
y              0
dtype: int64

------------------------------------
```

In [58]:

```python
# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=seed, stratify=y)
print("--- Train-Test Split ---\n")
print(f"Training set shape: {X_train.shape}, {y_train.shape}")
print(f"Testing set shape: {X_test.shape}, {y_test.shape}")
```

```
--- Train-Test Split ---

Training set shape: (36168, 15), (36168,)
Testing set shape: (9043, 15), (9043,)
```

In [ ]:

```python
# Evaluation function for model performance
def plot_confusion_matrix(y_true, y_pred, model_name):
    """
    This function plots a confusion matrix for the given true and p
    """
    cm = confusion_matrix(y_true, y_pred)
    tn, fp, fn, tp = cm.ravel()

    fig, ax = plt.subplots(figsize=(6, 6))
    fig.set_facecolor('#f5f7f6')

    sns.heatmap(
        cm,
        annot=True,
        fmt='d',
        cmap='Blues',
        cbar=False,
        annot_kws={"size": 16},
        ax=ax
```

```
    )

    ax.set_title(
        f'Confusion Matrix for {model_name}',
        fontsize=18, fontweight='bold', pad=20, loc='left', color='
    )
    ax.set_xlabel('Predicted Label', fontweight='bold', color='#555
    ax.set_ylabel('True Label', fontweight='bold', color='#555555')

    ax.xaxis.set_ticklabels(['No (0)', 'Yes (1)'])
    ax.yaxis.set_ticklabels(['No (0)', 'Yes (1)'])

    plt.tight_layout()
    plt.show()
```

In [60]:
```
# --- Experimenting Baseline Model Without `poutcome` ---
# Dropping `poutcome` feature
X_train_no_poutcome = X_train.drop(columns=['poutcome'], axis=1)
X_test_no_poutcome = X_test.drop(columns=['poutcome'], axis=1)

# Identifying categorical and numerical features for preprocessing
categorical_features_no_poutcome = X_train_no_poutcome.select_dtype
numerical_features_no_poutcome = X_train_no_poutcome.select_dtypes(
print("\nCategorical Features (without 'poutcome'):\n", categorical_
print("\nNumerical Features (without 'poutcome'):\n", numerical_fea
print("\n------------------------------------\n")

# Creating preprocessor for encoding categorical features and scali
preprocessor_no_poutcome = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_
        ('num', PowerTransformer(method='yeo-johnson'), numerical_f
    ])
print("\nPreprocessor (without 'poutcome'):\n", preprocessor_no_pou
print("\n------------------------------------\n")

# Creating a pipeline with SMOTE and Logistic Regression
pipeline_no_poutcome = ImbPipeline(steps=[
    ('preprocessor', preprocessor_no_poutcome),
    ('smote', SMOTE(random_state=seed)),
    ('classifier', LogisticRegression(class_weight='balanced', rand
])
print("\nPipeline (without 'poutcome'):\n", pipeline_no_poutcome)
print("\n------------------------------------\n")

# Training and evaluating the model without `poutcome`
pipeline_no_poutcome.fit(X_train_no_poutcome, y_train)
y_pred_no_poutcome = pipeline_no_poutcome.predict(X_test_no_poutcom
y_proba_no_poutcome = pipeline_no_poutcome.predict_proba(X_test_no_

# --- Experimenting Baseline Model With `poutcome` ---
# Identifying categorical and numerical features for preprocessing
categorical_features_with_poutcome = X_train.select_dtypes(include=
numerical_features_with_poutcome = X_train.select_dtypes(include=np
print("\nCategorical Features (with 'poutcome'):\n", categorical_fe
print("\nNumerical Features (with 'poutcome'):\n", numerical_featur
```

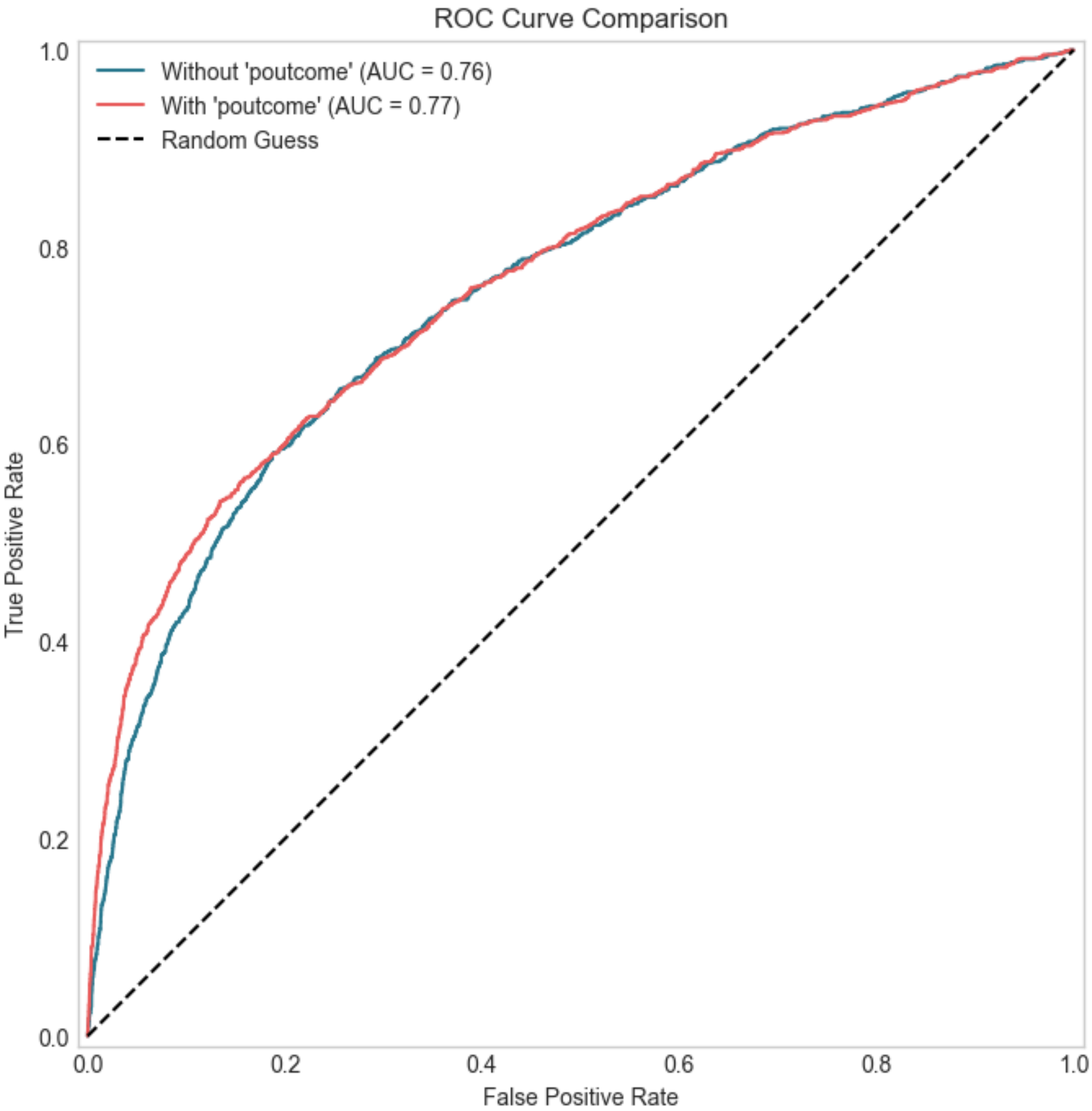
```
print("\n-------------------------------------\n")

# Creating preprocessor for encoding categorical features and scali
preprocessor_with_poutcome = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_
        ('num', PowerTransformer(method='yeo-johnson'), numerical_f
    ])
print("\nPreprocessor (with 'poutcome'):\n", preprocessor_with_pout
print("\n-------------------------------------\n")

# Creating a pipeline with SMOTE and Logistic Regression
pipeline_with_poutcome = ImbPipeline(steps=[
    ('preprocessor', preprocessor_with_poutcome),
    ('smote', SMOTE(random_state=seed)),
    ('classifier', LogisticRegression(class_weight='balanced', rand
])
print("\nPipeline (with 'poutcome'):\n", pipeline_with_poutcome)
print("\n-------------------------------------\n")

# Training and evaluating the model with `poutcome`
pipeline_with_poutcome.fit(X_train, y_train)
y_pred_with_poutcome = pipeline_with_poutcome.predict(X_test)
y_proba_with_poutcome = pipeline_with_poutcome.predict_proba(X_test

# --- Performance Comparison ---
print("\n--- Model Performance Comparison ---\n")
print("\nClassification Report (without 'poutcome'):\n")
print(classification_report(y_test, y_pred_no_poutcome, target_name
print("\nClassification Report (with 'poutcome'):\n")
print(classification_report(y_test, y_pred_with_poutcome, target_na

# Plotting ROC Curves for both models
fig, ax = plt.subplots(figsize=(8, 8))
RocCurveDisplay.from_predictions(y_test, y_proba_no_poutcome, name=
RocCurveDisplay.from_predictions(y_test, y_proba_with_poutcome, nam
ax.plot([0, 1], [0, 1], 'k--', label='Random Guess')
ax.set_title('ROC Curve Comparison')
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.legend()
ax.grid()
plt.show()

# Plotting Confusion Matrices for both models
plot_confusion_matrix(y_test, y_pred_no_poutcome, "Without 'poutcom
plot_confusion_matrix(y_test, y_pred_with_poutcome, "With 'poutcome

# Building a Comparison Dataframe
metrics = {
    'Model': ["Without 'poutcome'", "With 'poutcome'"],
    'Precision': [
        precision_score(y_test, y_pred_no_poutcome),
        precision_score(y_test, y_pred_with_poutcome)
    ],
    'Recall': [
```

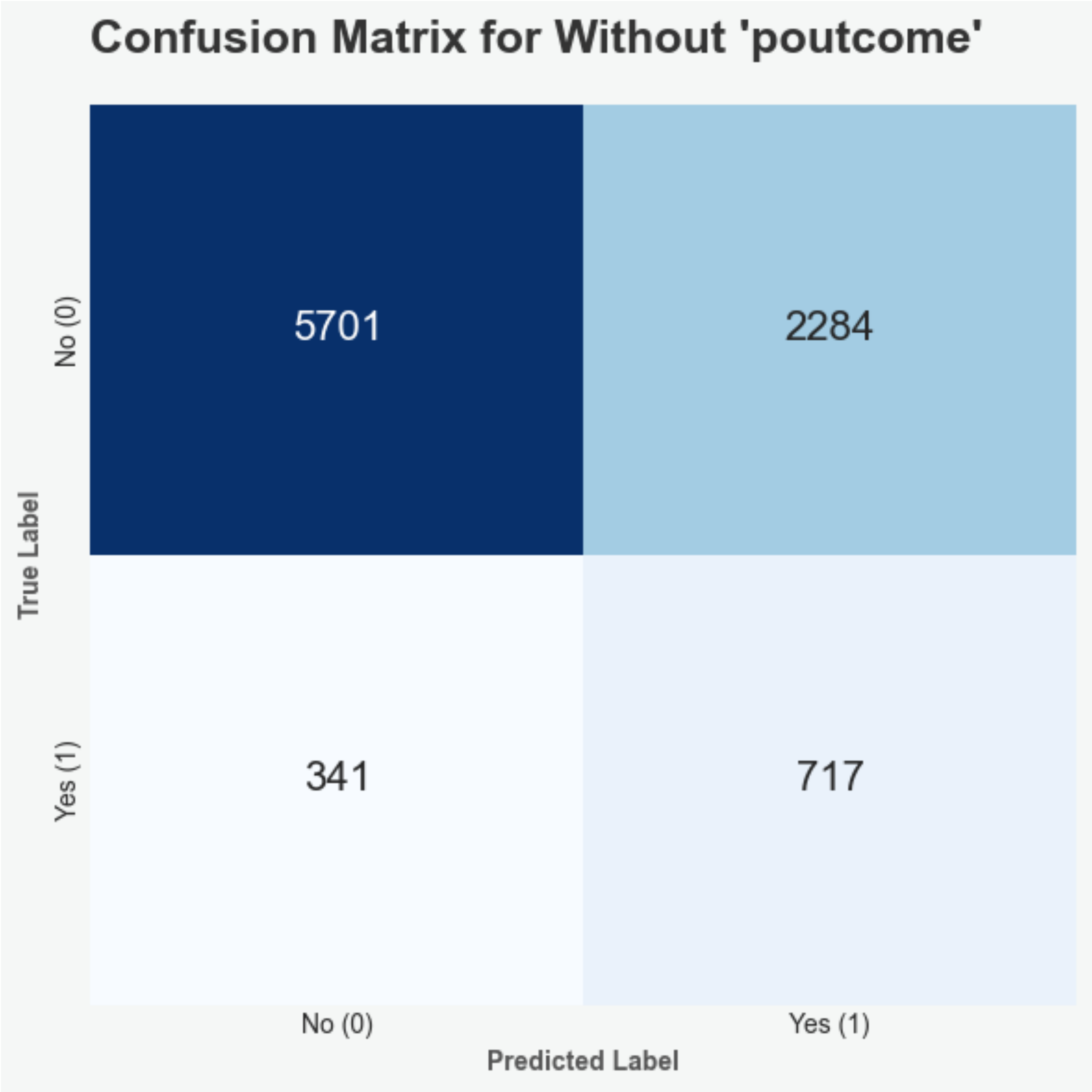
```
        recall_score(y_test, y_pred_no_poutcome),
        recall_score(y_test, y_pred_with_poutcome)
    ],
    'F1-Score': [
        f1_score(y_test, y_pred_no_poutcome),
        f1_score(y_test, y_pred_with_poutcome)
    ],
    'ROC AUC': [
        roc_auc_score(y_test, y_proba_no_poutcome),
        roc_auc_score(y_test, y_proba_with_poutcome)
    ]
}
comparison_df = pd.DataFrame(metrics)
print("\nPerformance Comparison DataFrame:\n")
display(comparison_df.style.format({'Precision': '{:.2f}', 'Recall'
```

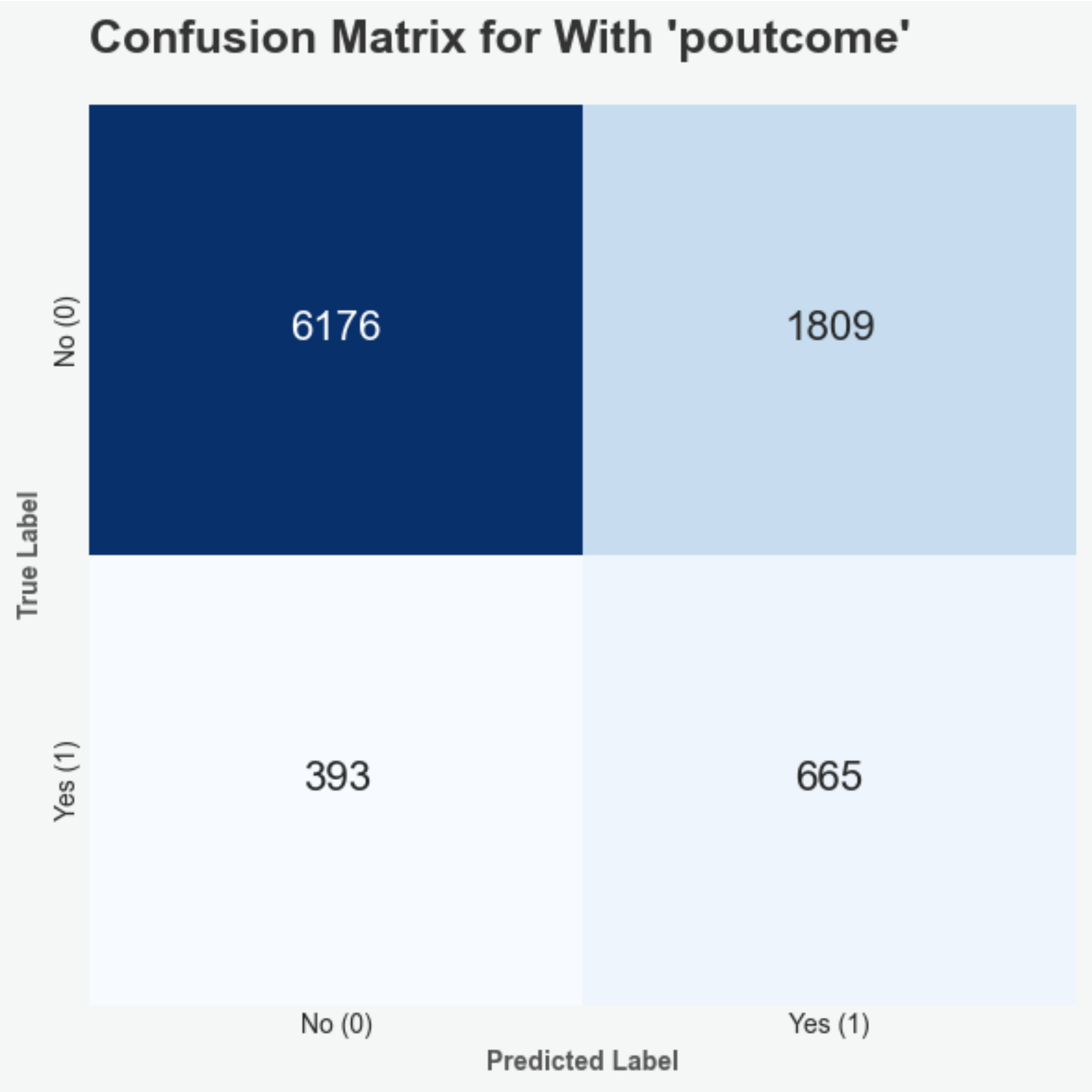
```
Categorical Features (without 'poutcome'):
 Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'month'],
      dtype='object')

Numerical Features (without 'poutcome'):
 Index(['age', 'balance', 'day_of_week', 'campaign', 'pdays', 'previ
ous'], dtype='object')

------------------------------------



Preprocessor (without 'poutcome'):
 ColumnTransformer(transformers=[('cat', OneHotEncoder(handle_unknow
n='ignore'),
                                 Index(['job', 'marital', 'educatio
n', 'default', 'housing', 'loan', 'contact',
       'month'],
      dtype='object')),
                                ('num', PowerTransformer(),
                                 Index(['age', 'balance', 'day_of_we
ek', 'campaign', 'pdays', 'previous'], dtype='object'))])

------------------------------------



Pipeline (without 'poutcome'):
 Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  OneHotEncoder(hand
le_unknown='ignore'),
                                                  Index(['job', 'mar
ital', 'education', 'default', 'housing', 'loan', 'contact',
       'month'],
      dtype='object')),
                                                 ('num', PowerTransf
ormer(),
                                                  Index(['age', 'bal
ance', 'day_of_week', 'campaign', 'pdays', 'previous'], dtype='objec
```

```
t'))])),
                ('smote', SMOTE(random_state=42)),
                ('classifier',
                 LogisticRegression(class_weight='balanced', max_ite
r=1000,
                                    random_state=42))])

------------------------------------


Categorical Features (with 'poutcome'):
 Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'month', 'poutcome'],
      dtype='object')

Numerical Features (with 'poutcome'):
 Index(['age', 'balance', 'day_of_week', 'campaign', 'pdays', 'previ
ous'], dtype='object')

------------------------------------


Preprocessor (with 'poutcome'):
 ColumnTransformer(transformers=[('cat', OneHotEncoder(handle_unknow
n='ignore'),
                                 Index(['job', 'marital', 'educatio
n', 'default', 'housing', 'loan', 'contact',
       'month', 'poutcome'],
      dtype='object')),
                                ('num', PowerTransformer(),
                                 Index(['age', 'balance', 'day_of_we
ek', 'campaign', 'pdays', 'previous'], dtype='object'))])

------------------------------------


Pipeline (with 'poutcome'):
 Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('cat',
                                                  OneHotEncoder(hand
le_unknown='ignore'),
                                                  Index(['job', 'mar
ital', 'education', 'default', 'housing', 'loan', 'contact',
       'month', 'poutcome'],
      dtype='object')),
                                                 ('num', PowerTransf
ormer(),
                                                  Index(['age', 'bal
ance', 'day_of_week', 'campaign', 'pdays', 'previous'], dtype='objec
t'))])),
                ('smote', SMOTE(random_state=42)),
                ('classifier',
                 LogisticRegression(class_weight='balanced', max_ite
r=1000,
                                    random_state=42))])
```

```
------------------------------------

--- Model Performance Comparison ---

Classification Report (without 'poutcome'):
              precision    recall  f1-score   support

          no       0.94      0.71      0.81      7985
         yes       0.24      0.68      0.35      1058

    accuracy                           0.71      9043
   macro avg       0.59      0.70      0.58      9043
weighted avg       0.86      0.71      0.76      9043

Classification Report (with 'poutcome'):
              precision    recall  f1-score   support

          no       0.94      0.77      0.85      7985
         yes       0.27      0.63      0.38      1058

    accuracy                           0.76      9043
   macro avg       0.60      0.70      0.61      9043
weighted avg       0.86      0.76      0.79      9043
```


ROC Curve Comparison
Without 'poutcome' (AUC = 0.76)
With 'poutcome' (AUC = 0.77)
Random Guess
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Confusion Matrix for Without 'poutcome'
5701
2284
341
717
True Label
No (0)
Yes (1)
No (0)
Yes (1)
Predicted Label




```
Performance Comparison DataFrame:
```

	Model	Precision	Recall	F1-Score	ROC AUC
0	Without 'poutcome'	0.24	0.68	0.35	0.76
1	With 'poutcome'	0.27	0.63	0.38	0.77

- **Performance Evaluation**
  - Although the improvement is not massive, the model that includes the `poutcome` feature demonstrated superior performance on our key metrics. It achieved a higher **F1-Score (0.38 vs. 0.35)**, which indicates a better balance between Precision and Recall. While its Recall was slightly lower, its **Precision** was higher, resulting in significantly fewer False Positive errors (1,809 vs. 2,284).
- **Business POV**
  - From a business perspective, an effective marketing campaign must balance two objectives: maximizing the number of successful sales

(**Recall**) while minimizing resources spent on uninterested clients (**Precision**). The **F1-Score** is the ideal metric for this scenario as it measures the overall effectiveness of the model's generated call list by finding a harmony between these two goals. Since the model *with* `poutcome` achieved a higher F1-Score, it provides more business value. Therefore, we will keep this feature for our final model.

Feature Engineering

We will maintain the `poutcome` feature in the dataset. In this section, we will fill in missing data with the `unknown` label across categories. We will also drop the `duration` feature due to data leakage and re-engineer quasi-categorical features.

In [61]:
```
# Creating a copy of the model dataframe for feature engineering
df_engineered = df.copy()

# Dropping the `duration` feature due to data leakage
df_engineered.drop(columns=['duration'], axis=1, inplace=True)

# Replacing missing values with `unknown`
df_engineered[categorical_features] = df_engineered[categorical_fea

print("\n--- Initial Cleaning Complete ---\n")
print("Feature `duration` dropped and NaNs filled with 'unknown'.\n
print("Original Dataframe:\n")
display(df.head(5))
print("\nEngineered Dataframe:\n")
display(df_engineered.head(5))
print("\n-------------------------------------\n")
```

```
--- Initial Cleaning Complete ---

Feature `duration` dropped and NaNs filled with 'unknown'.

Original Dataframe:
```

	age	job	marital	education	default	balance	housing	loan	con
0	58	management	married	tertiary	no	2143	yes	no	
1	44	technician	single	secondary	no	29	yes	no	
2	33	entrepreneur	married	secondary	no	2	yes	yes	
3	47	blue-collar	married	NaN	no	1506	yes	no	
4	33	NaN	single	NaN	no	1	no	no	

```
Engineered Dataframe:
```

	age	job	marital	education	default	balance	housing	loan	co
0	58	management	married	tertiary	no	2143	yes	no	unk
1	44	technician	single	secondary	no	29	yes	no	unk
2	33	entrepreneur	married	secondary	no	2	yes	yes	unk
3	47	blue-collar	married	unknown	no	1506	yes	no	unk
4	33	unknown	single	unknown	no	1	no	no	unk

In [62]:
```
# Reviewing descriptive statistics for `pdays` and `previous` featu
df[['pdays', 'previous']].describe().T
```

Out[62]:

	count	mean	std	min	25%	50%	75%	max
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.0	871.0
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.0	275.0

- **EDA Insights**
  - During EDA, we observed that `pdays` and `previous` features have an overwhelming number of instances at the same value (`-1` and `0`). Essentially, these features don't really behave that much as continuous features.
  - In an attempt to improve performance, we will engineer these features by transforming them into **binary features** and then dropping the original columns.
- **New Features**
  - Instead of `pdays` , we will create a new feature called `was_previously_contacted` where values other than `-1` will be labeled as `yes` .
  - Likewise, we will transform the `previous` feature into a feature called `had_previous_contact` , where values other than `0` will be labeled as `yes` .

In [63]:
```
# Transforming `pdays` and `previous` into binary features
df_engineered['was_previously_contacted'] = np.where(df_engineered[
df_engineered['had_previous_contact'] = np.where(df_engineered['pre
df_engineered.drop(columns=['pdays', 'previous'], axis=1, inplace=T
print("\n--- Engineering `pdays` and `previous` into binary feature
print("Original Dataframe:\n")
display(df[['pdays', 'previous']].head(5))
```

```
print("\nEngineered Dataframe:\n")
display(df_engineered[['was_previously_contacted', 'had_previous_co
print("\n------------------------------------\n")
```

```
--- Engineering `pdays` and `previous` into binary features and drop
ping original columns ---

Original Dataframe:
```

	pdays	previous
0	-1	0
1	-1	0
2	-1	0
3	-1	0
4	-1	0

```
Engineered Dataframe:
```

	was_previously_contacted	had_previous_contact
0	no	no
1	no	no
2	no	no
3	no	no
4	no	no

```
------------------------------------
```

- **Dealing with Mislabeled Features**
  - Our EDA also revealed that the feature `day_of_week` is misleading, as it clearly refers to the day of the month. We will rename it to a more accurate designation. We will also stop treating it as a continuous feature and normalizing it within the pipeline. Instead, we will handle it as a **categorical feature**. The idea is to convert it to a string type and allow the model to learn the importance of specific days without assuming any ordered relationship between them.

In [64]:
```
# Renaming `day_of_week` to `day_of_month` and treating it as a cat
df_engineered.rename(columns={'day_of_week': 'day_of_month'}, inpla
df_engineered['day_of_month'] = df_engineered['day_of_month'].astyp
print("\n--- Renaming `day_of_week` to `day_of_month` and convertin
print("Original Dataframe:\n")
print("Data Type:", df['day_of_week'].dtype)
display(df[['day_of_week']].head(5))
print("\nEngineered Dataframe:\n")
```

```
print("Data Type:", df_engineered['day_of_month'].dtype)
display(df_engineered[['day_of_month']].head(5))
print("\n------------------------------------\n")
```

```
--- Renaming `day_of_week` to `day_of_month` and converting to categ
orical feature ---

Original Dataframe:

Data Type: int64
```

	day_of_week
0	5
1	5
2	5
3	5
4	5

```
Engineered Dataframe:

Data Type: object
```

	day_of_month
0	5
1	5
2	5
3	5
4	5

```
------------------------------------
```

Before moving on to the next phase, we can run a quick sanity check by using our `describe_df` function to see if the post-engineered dataframe is how we initially planned.

In [65]:
```
# Checking the engineered dataframe
describe_df(df_engineered)
```

```
DataFrame shape: (45211, 16)

45,211 samples

16 attributes

Categorical Features:
job, marital, education, default, housing, loan, contact, day_of_mon
th, month, poutcome, y, was_previously_contacted, had_previous_conta
ct
```

```
Continuous Features:
age, balance, campaign

Binary (0 or 1) Features:
None

Data Types:
age                         int64
job                        object
marital                    object
education                  object
default                    object
balance                     int64
housing                    object
loan                       object
contact                    object
day_of_month               object
month                      object
campaign                    int64
poutcome                   object
y                          object
was_previously_contacted   object
had_previous_contact       object
dtype: object

Missing Data Percentage:
age                        0.0%
job                        0.0%
marital                    0.0%
education                  0.0%
default                    0.0%
balance                    0.0%
housing                    0.0%
loan                       0.0%
contact                    0.0%
day_of_month               0.0%
month                      0.0%
campaign                   0.0%
poutcome                   0.0%
y                          0.0%
was_previously_contacted   0.0%
had_previous_contact       0.0%
dtype: object

Duplicates: 16

Categorical Feature Cardinality:
day_of_month               31
job                        12
month                      12
education                   4
poutcome                    4
marital                     3
contact                     3
default                     2
housing                     2
```

```
loan                        2
y                           2
was_previously_contacted    2
had_previous_contact        2
dtype: int64

Features with Zero Variance: None

Features with Negative Values: balance

Statistical Summary:
```

	count	mean	std	min	25%	50%	75%
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.0
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.0 1
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.0

```
DataFrame Head:
```

	age	job	marital	education	default	balance	housing	loan	co
0	58	management	married	tertiary	no	2143	yes	no	unk
1	44	technician	single	secondary	no	29	yes	no	unk
2	33	entrepreneur	married	secondary	no	2	yes	yes	unk
3	47	blue-collar	married	unknown	no	1506	yes	no	unk
4	33	unknown	single	unknown	no	1	no	no	unk

```
DataFrame Tail:
```

	age	job	marital	education	default	balance	housing	loa
45206	51	technician	married	tertiary	no	825	no	n
45207	71	retired	divorced	primary	no	1729	no	n
45208	72	retired	married	secondary	no	5715	no	n
45209	57	blue-collar	married	secondary	no	668	no	n
45210	37	entrepreneur	married	secondary	no	2971	no	n

Modeling

With our data fully preprocessed and engineered, we now proceed to the modeling phase. In this section, we'll train and evaluate a variety of classification algorithms to find the best performer for our business problem. Each model will be evaluated using a stratified cross-validation strategy to ensure fair and robust comparison.

In [66]:
```
# Removing `y` from categorical_features list
categorical_features.remove('y')

# Separating features and target variable
X_engineered = df_engineered.drop('y', axis=1)
y_engineered = df_engineered['y'].map({'yes': 1, 'no': 0}) # Encodi

print("--- Features and Target Variable ---")
print("\nFeatures:\n")
print(X_engineered.shape)
print('\n')
print(X_engineered.head())
print("\nTarget Variable:\n")
print(y_engineered.shape)
print('\n')
print(y_engineered.head())
print("\n------------------------------------\n")
print("Missing Data Check:\n")
print(df_engineered.isnull().sum())
print("\n------------------------------------\n")
```

```
--- Features and Target Variable ---

Features:

(45211, 15)


   age           job  marital  education default  balance housing lo
an  \
0   58    management  married   tertiary      no     2143     yes
no
1   44    technician   single  secondary      no       29     yes
no
2   33  entrepreneur  married  secondary      no        2     yes   y
es
3   47   blue-collar  married    unknown      no     1506     yes
no
4   33       unknown   single    unknown      no        1      no
no

   contact day_of_month month  campaign poutcome was_previously_cont
acted  \
0  unknown            5   may         1  unknown
no
1  unknown            5   may         1  unknown
no
2  unknown            5   may         1  unknown
no
3  unknown            5   may         1  unknown
no
```

```
4   unknown             5    may         1   unknown
no

  had_previous_contact
0                    no
1                    no
2                    no
3                    no
4                    no

Target Variable:

(45211,)


0    0
1    0
2    0
3    0
4    0
Name: y, dtype: int64

------------------------------------

Missing Data Check:

age                         0
job                         0
marital                     0
education                   0
default                     0
balance                     0
housing                     0
loan                        0
contact                     0
day_of_month                0
month                       0
campaign                    0
poutcome                    0
y                           0
was_previously_contacted    0
had_previous_contact        0
dtype: int64

------------------------------------
```

In [67]:

```python
# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_engineered, y_engineered, test_size=0.2, random_state=seed, s

print("--- Train-Test Split ---\n")
print(f"Training set shape: {X_train.shape}, {y_train.shape}")
print(f"Testing set shape: {X_test.shape}, {y_test.shape}")
```

```
--- Train-Test Split ---

Training set shape: (36168, 15), (36168,)
Testing set shape: (9043, 15), (9043,)
```

In [68]:

```
# --- Model Building and Evaluation ---
# Identifying categorical and numerical features for preprocessing
categorical_features_engineered = X_train.select_dtypes(include=['o
numerical_features_engineered = X_train.select_dtypes(include=np.nu
print("\nCategorical Features (Engineered):\n", categorical_feature
print("\nNumerical Features (Engineered):\n", numerical_features_en
print("\n------------------------------------\n")

# Creating preprocessor for encoding categorical features and scali
preprocessor_engineered = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_
        ('num', PowerTransformer(method='yeo-johnson'), numerical_f
    ])
print("\nPreprocessor (Engineered):\n", preprocessor_engineered)
print("\n------------------------------------\n")

# Defining models to compare
models = {
    "Logistic Regression": LogisticRegression(class_weight='balance
    "Random Forest": RandomForestClassifier(class_weight='balanced'
    "Gradient Boosting": GradientBoostingClassifier(random_state=se
    "XGBoost": XGBClassifier(eval_metric='logloss', random_state=se
    "LightGBM": LGBMClassifier(random_state=seed, verbose=-1)
}

# Defining Cross-Validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=seed)

# Evaluating each model using cross-validation
results = []
roc_plot_data = []

print("\n--- Model Evaluation with Cross-Validation ---\n")
for model_name, model in models.items():
    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor_engineered),
        ('smote', SMOTE(random_state=seed)),
        ('classifier', model)
    ])

    start_time = time.time()

    cv_results = cross_validate(
        pipeline, X_train, y_train,
        cv=cv,
        scoring=['precision', 'recall', 'f1', 'roc_auc'],
        return_train_score=False)

    end_time = time.time()
    training_time = end_time - start_time
```

```
    # Store results
    results.append({
        'Model': model_name,
        'Precision': np.mean(cv_results['test_precision']),
        'Recall': np.mean(cv_results['test_recall']),
        'F1-Score': np.mean(cv_results['test_f1']),
        'ROC AUC': np.mean(cv_results['test_roc_auc']),
        'Training Time (s)': training_time})

    # Fit the model to get ROC curve data
    pipeline.fit(X_train, y_train)
    y_proba = pipeline.predict_proba(X_test)[:, 1]
    y_pred = pipeline.predict(X_test)
    plot_confusion_matrix(y_test, y_pred, model_name)
    roc_plot_data.append({
        'model_name': model_name,
        'y_true': y_test,
        'y_proba': pipeline.predict_proba(X_test)[:, 1]
    })
    print(f"{model_name} evaluated in {training_time:.2f} seconds."

# Creating a results dataframe
results_df = pd.DataFrame(results)
print("\nCross-Validation Results:\n")
display(results_df.style.format({'Precision': '{:.2f}', 'Recall': '
                                 'ROC AUC': '{:.2f}', 'Training Tim

# Plotting ROC Curves for all models
fig, ax = plt.subplots(figsize=(10, 8))
fig.set_facecolor('#f5f7f6')
ax.plot([0, 1], [0, 1], 'k--', label='Random Guess')
for data in roc_plot_data:
    RocCurveDisplay.from_predictions(
        data['y_true'], data['y_proba'], name=data['model_name'], a
plt.title('ROC Curve Comparison for All Models')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
plt.show()
```

```
Categorical Features (Engineered):
 Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'day_of_month', 'month', 'poutcome', 'was_previously_contacte
d',
       'had_previous_contact'],
      dtype='object')

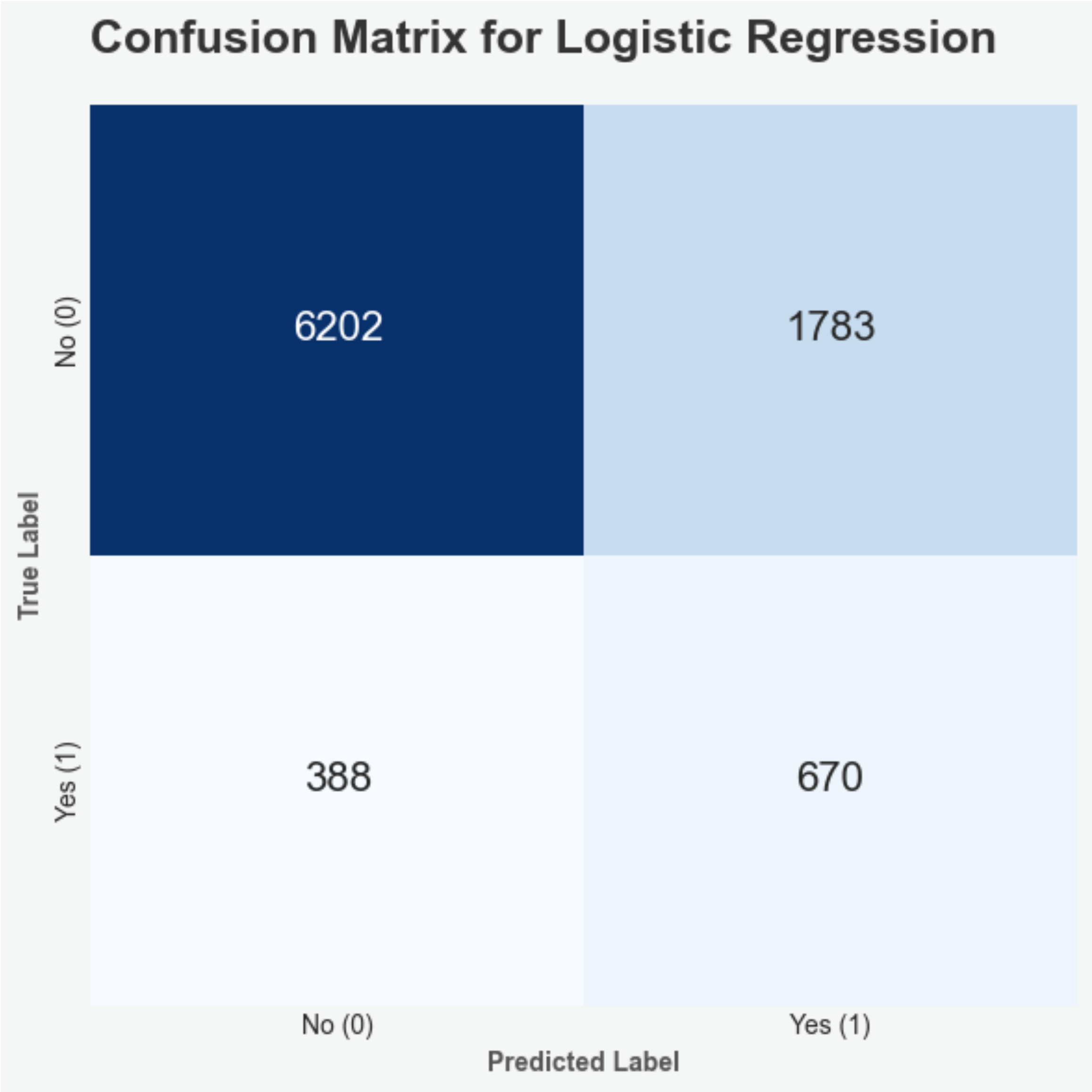
Numerical Features (Engineered):
 Index(['age', 'balance', 'campaign'], dtype='object')

------------------------------------

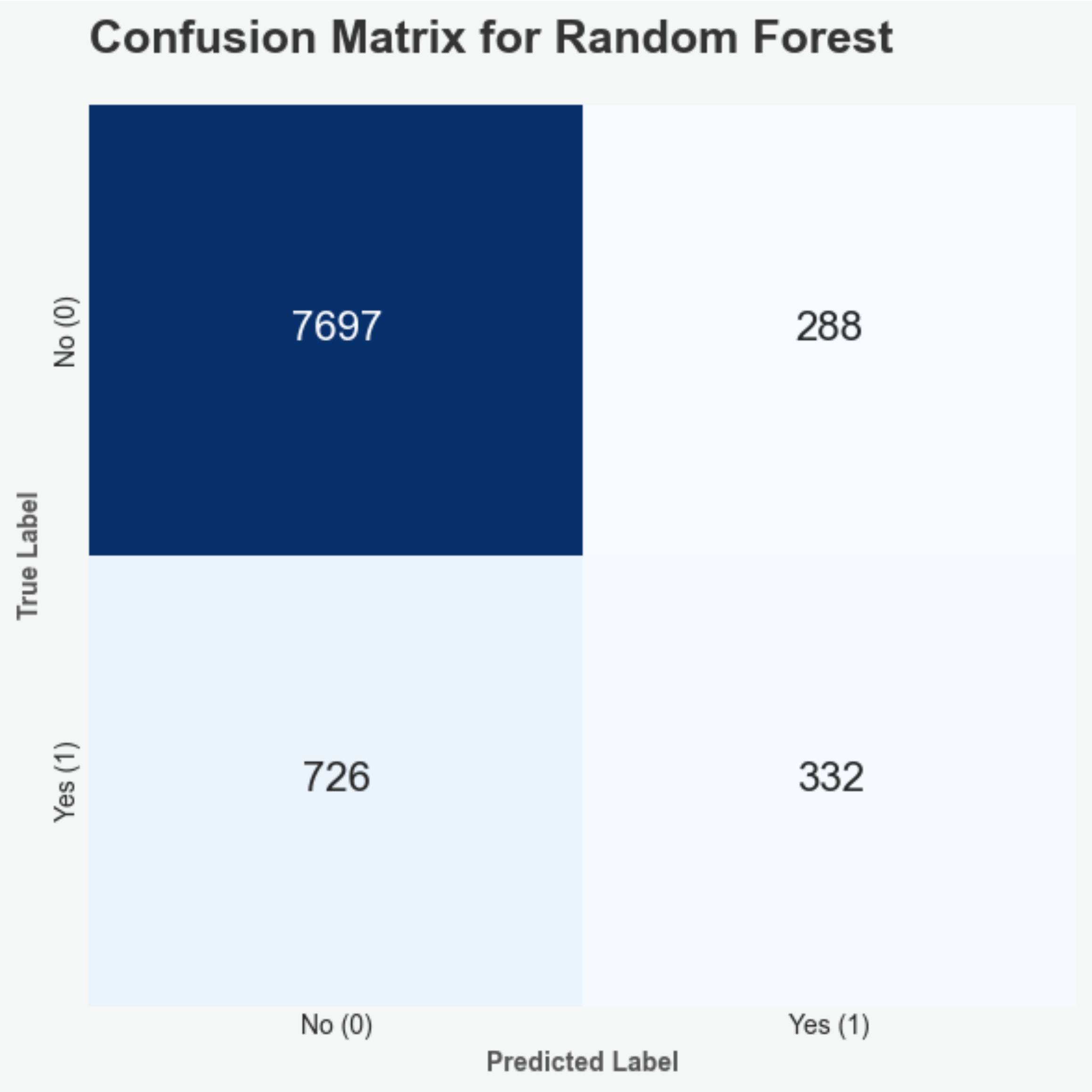

Preprocessor (Engineered):
 ColumnTransformer(transformers=[('cat', OneHotEncoder(handle_unknow
n='ignore'),
                                 Index(['job', 'marital', 'educatio
n', 'default', 'housing', 'loan', 'contact',
       'day_of_month', 'month', 'poutcome', 'was_previously_contacte
d',
       'had_previous_contact'],
      dtype='object')),
                                ('num', PowerTransformer(),
                                 Index(['age', 'balance', 'campaig
n'], dtype='object'))])

------------------------------------

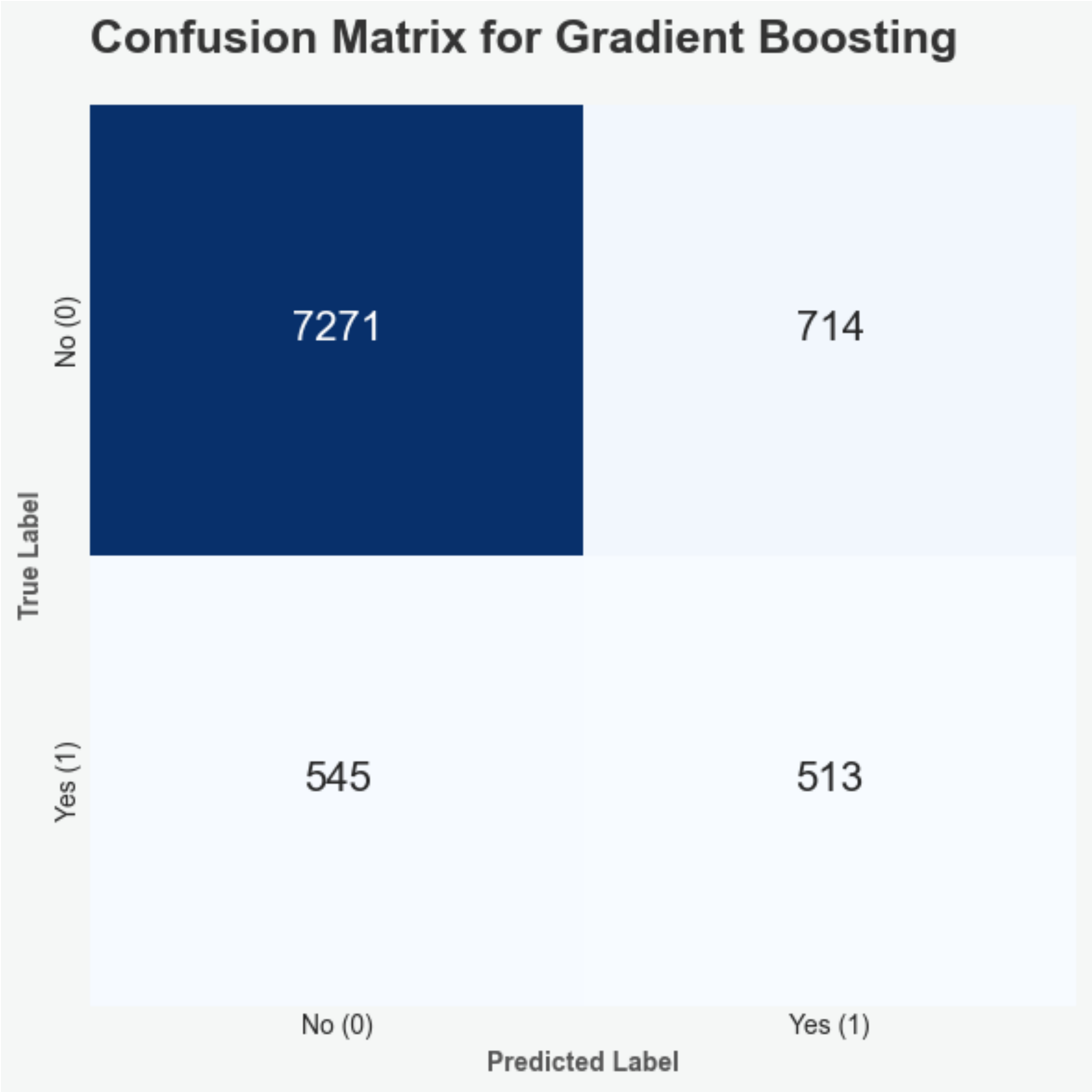

--- Model Evaluation with Cross-Validation ---
```



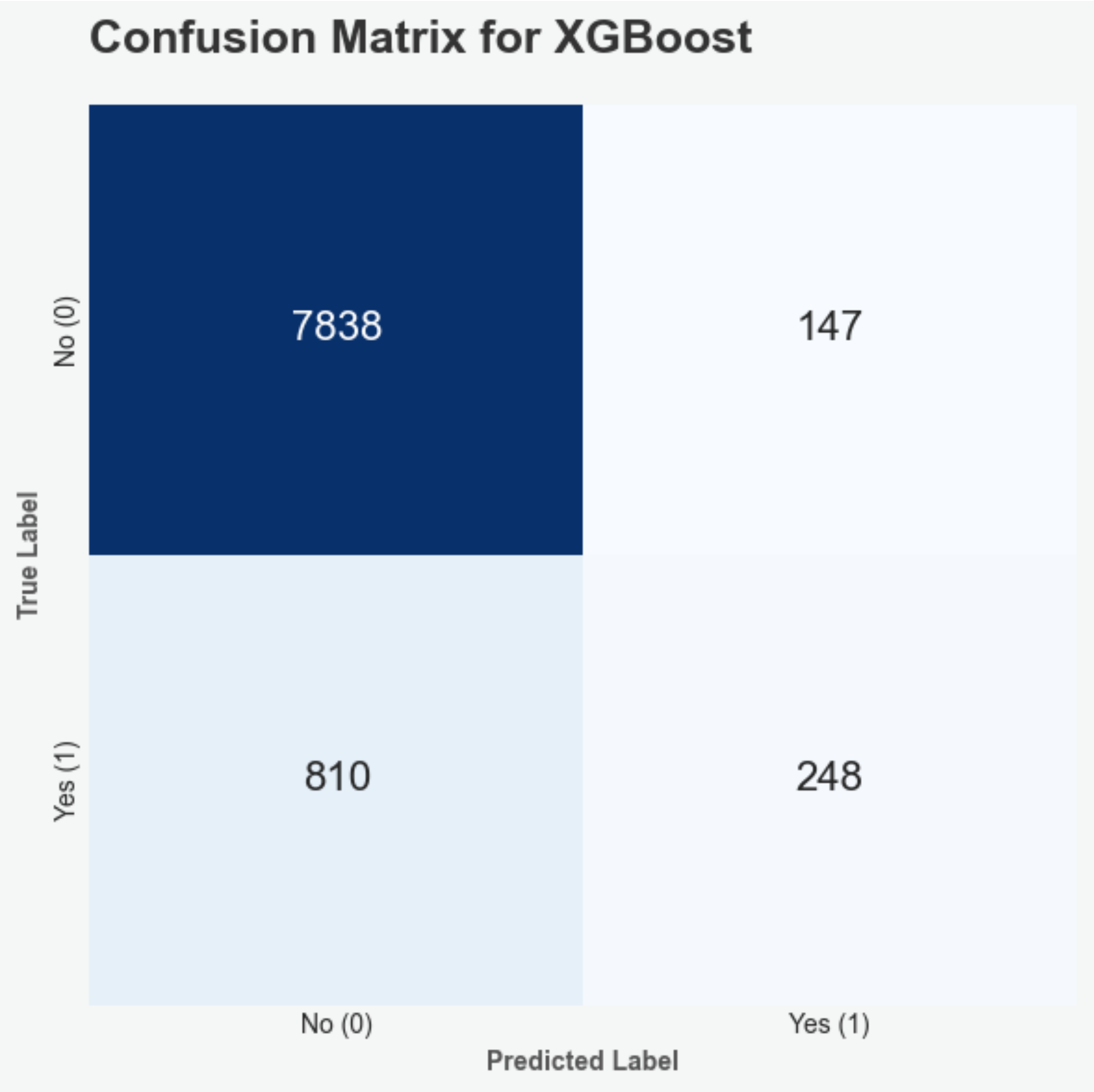

```
Logistic Regression evaluated in 3.03 seconds.
```



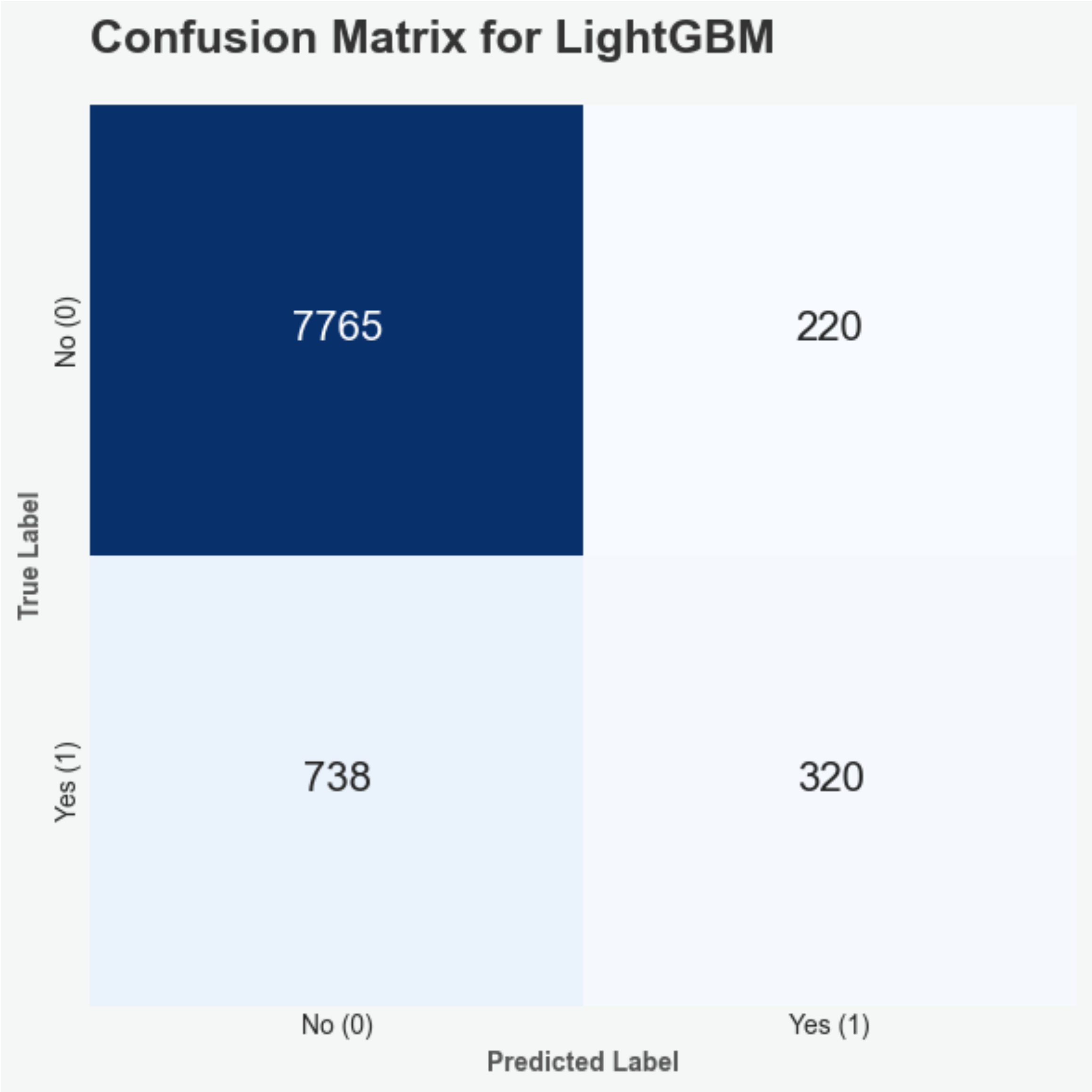

```
Random Forest evaluated in 106.48 seconds.
```




```
Gradient Boosting evaluated in 38.54 seconds.
```



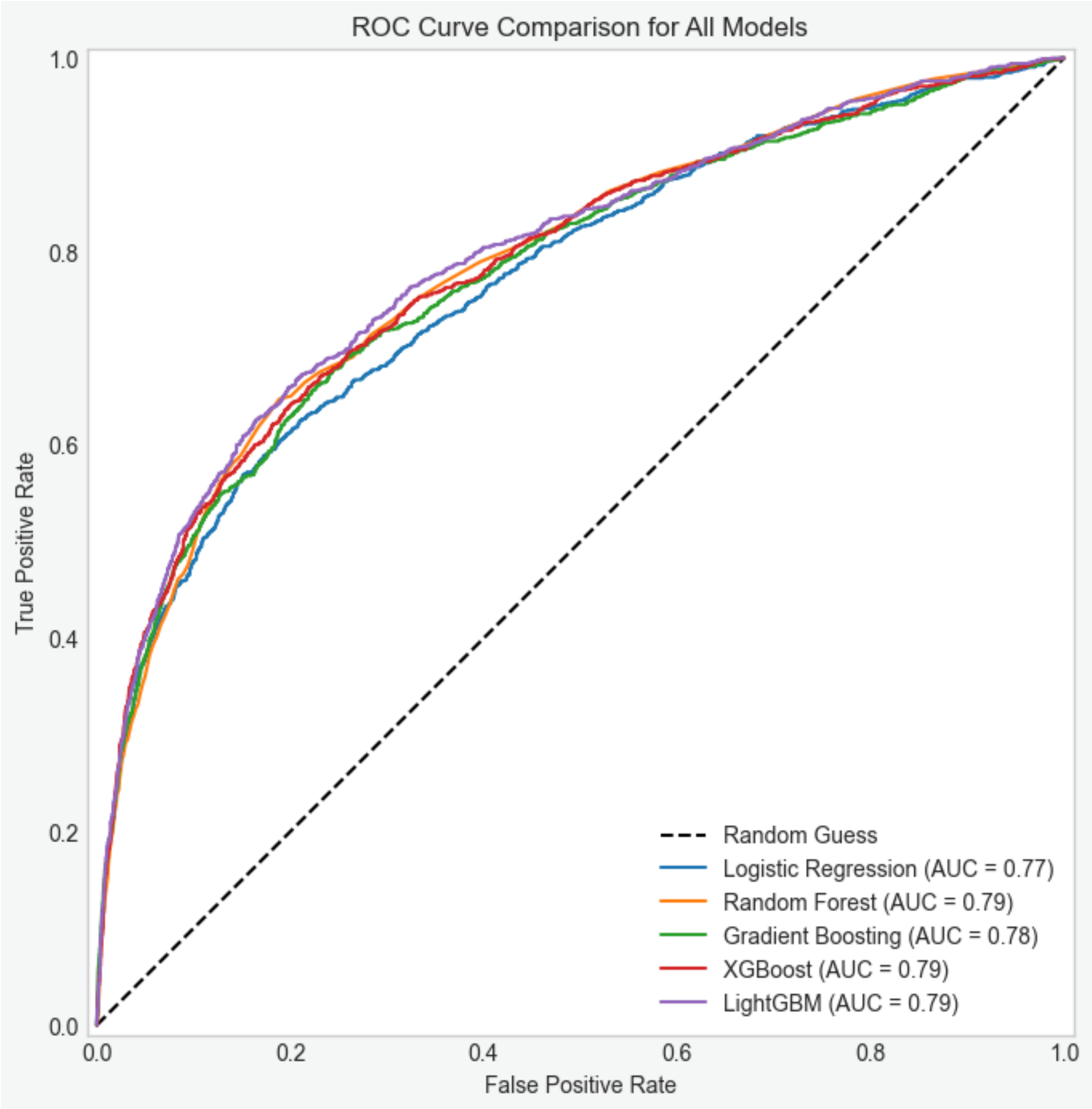
XGBoost evaluated in 4.76 seconds.




```
LightGBM evaluated in 5.49 seconds.

Cross-Validation Results:
```

	Model	Precision	Recall	F1-Score	ROC AUC	Training Time (s)
0	Logistic Regression	0.27	0.63	0.38	0.76	3.03
1	Random Forest	0.52	0.30	0.38	0.78	106.48
2	Gradient Boosting	0.42	0.45	0.43	0.77	38.54
3	XGBoost	0.60	0.22	0.33	0.78	4.76
4	LightGBM	0.56	0.29	0.38	0.79	5.49



- The Gradient Boosting has the highest F1 Score, making it the most balanced model of the set in regards to Recall and Precision. However, it is one of the slowest models in regards to training time.

- The XGBoost achieved the highest Precision at 0.60. It has the fewest False Positiver errors, only 147. In practice, this model helps us avoid calling clients who would be more likely to say *no*, but it also misses the most potential customers, given the lowest Recall (meaning a higher number of False Negatives).

- The LightGBM model has the highest ROC AUC score, which in practice means the model is best at ranking customers from most to least likely to subscribe. It has has a good F1-Score.

Tuning Models

In order to achieve higher performance, we will fine-tune the LightGBM and

XGBoost models with Optuna. The goal is to find the ideal set of hyperparameters to increase performance. Although the Gradient Boosting model have us the highest F1-Score, it was also one of the slowest models. By fine-tuning the LightGBM and XGBoost, we aim at surpassing the Gradient Boosting model at a lower cost.

In [69]:
```
def objective_lgbm(trial):
    """
    This is the objective function that Optuna will optimize.
    A 'trial' is a single run of the model with a specific set of h
    """
    params = {
        'objective': 'binary',
        'metric': 'binary_logloss',
        'n_estimators': trial.suggest_int('n_estimators', 200, 2000
        'learning_rate': trial.suggest_float('learning_rate', 0.01,
        'num_leaves': trial.suggest_int('num_leaves', 20, 3000, ste
        'max_depth': trial.suggest_int('max_depth', 3, 12),
        'min_child_samples': trial.suggest_int('min_child_samples',
        'subsample': trial.suggest_float('subsample', 0.6, 1.0),
        'colsample_bytree': trial.suggest_float('colsample_bytree',
        'reg_alpha': trial.suggest_float('reg_alpha', 1e-8, 10.0, l
        'reg_lambda': trial.suggest_float('reg_lambda', 1e-8, 10.0,
        'random_state': 42,
        'n_jobs': -1,
        'verbose': -1
    }

    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor_engineered),
        ('smote', SMOTE(random_state=seed)),
        ('classifier', LGBMClassifier(**params))
    ])

    cv_strategy = StratifiedKFold(n_splits=5, shuffle=True, random_
    score = cross_val_score(
        pipeline, X_train, y_train, cv=cv_strategy, scoring='f1', n_
    ).mean()
    return score

study_lgbm = optuna.create_study(direction='maximize', study_name='
print("\n--- Starting Hyperparameter Optimization for LightGBM ---\
study_lgbm.optimize(objective_lgbm, n_trials=100, show_progress_bar
print("\n--- Hyperparameter Optimization Complete ---\n")
print("Best trial:")
trial = study_lgbm.best_trial
print(f"  Value: {trial.value}")
print("  Params: ")
for key, value in trial.params.items():
    print(f"    {key}: {value}")
```

```
[I 2025-09-16 19:24:59,807] A new study created in memory with name:
LGBM Classifier Optimization
```

```
--- Starting Hyperparameter Optimization for LightGBM ---

Best trial: 0. Best value: 0.354034:   1%|          | 1/100 [03:21<
5:33:04, 201.86s/it]
[I 2025-09-16 19:28:21,672] Trial 0 finished with value: 0.354034359
2253018 and parameters: {'n_estimators': 2000, 'learning_rate': 0.14
375029681578794, 'num_leaves': 500, 'max_depth': 12, 'min_child_samp
les': 39, 'subsample': 0.6417816153031995, 'colsample_bytree': 0.606
7933156559204, 'reg_alpha': 1.3818036142649898e-07, 'reg_lambda': 5.
189917246351253e-07}. Best is trial 0 with value: 0.354034359225301
8.
Best trial: 1. Best value: 0.360631:   2%|▏         | 2/100 [03:29<
2:22:59, 87.54s/it]
[I 2025-09-16 19:28:29,193] Trial 1 finished with value: 0.360630731
7534324 and parameters: {'n_estimators': 700, 'learning_rate': 0.119
6976415985506, 'num_leaves': 880, 'max_depth': 5, 'min_child_sample
s': 125, 'subsample': 0.6491331373259933, 'colsample_bytree': 0.7716
456046366084, 'reg_alpha': 2.498906002211727e-07, 'reg_lambda': 6.21
6877885285744}. Best is trial 1 with value: 0.3606307317534324.
Best trial: 1. Best value: 0.360631:   3%|▎         | 3/100 [03:49<
1:32:03, 56.94s/it]
[I 2025-09-16 19:28:49,712] Trial 2 finished with value: 0.349282527
8770932 and parameters: {'n_estimators': 1500, 'learning_rate': 0.02
2155257192552694, 'num_leaves': 480, 'max_depth': 7, 'min_child_samp
les': 95, 'subsample': 0.6157932082487831, 'colsample_bytree': 0.818
1290821779695, 'reg_alpha': 4.124725121788372, 'reg_lambda': 3.70121
8376466825e-05}. Best is trial 1 with value: 0.3606307317534324.
Best trial: 1. Best value: 0.360631:   4%|▍         | 4/100 [04:11<
1:08:41, 42.93s/it]
[I 2025-09-16 19:29:11,169] Trial 3 finished with value: 0.358456143
67742484 and parameters: {'n_estimators': 700, 'learning_rate': 0.15
134906129179576, 'num_leaves': 620, 'max_depth': 12, 'min_child_samp
les': 165, 'subsample': 0.6003054300554304, 'colsample_bytree': 0.89
46444567690156, 'reg_alpha': 4.292096398079292e-08, 'reg_lambda': 0.
0014931129339135595}. Best is trial 1 with value: 0.360630731753432
4.
Best trial: 1. Best value: 0.360631:   5%|▌         | 5/100 [04:45<
1:02:43, 39.61s/it]
[I 2025-09-16 19:29:44,899] Trial 4 finished with value: 0.353601003
02480896 and parameters: {'n_estimators': 1400, 'learning_rate': 0.1
6747128946878984, 'num_leaves': 2060, 'max_depth': 8, 'min_child_sam
ples': 135, 'subsample': 0.8632876977551023, 'colsample_bytree': 0.8
741264000477884, 'reg_alpha': 0.0011605723760328911, 'reg_lambda':
0.4372549452649395}. Best is trial 1 with value: 0.3606307317534324.
Best trial: 5. Best value: 0.412109:   6%|▌         | 6/100 [05:22<
1:00:58, 38.92s/it]
[I 2025-09-16 19:30:22,472] Trial 5 finished with value: 0.412109227
4485245 and parameters: {'n_estimators': 500, 'learning_rate': 0.014
562565097287225, 'num_leaves': 2800, 'max_depth': 10, 'min_child_sam
ples': 23, 'subsample': 0.8616474280028409, 'colsample_bytree': 0.94
80201419537508, 'reg_alpha': 0.00402565505746664, 'reg_lambda': 1.98
3938231210734e-06}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:   7%|▋         | 7/100 [06:31<
1:15:23, 48.64s/it]
```

```
[I 2025-09-16 19:31:31,126] Trial 6 finished with value: 0.355017796
88135804 and parameters: {'n_estimators': 1500, 'learning_rate': 0.1
6385527042693004, 'num_leaves': 2620, 'max_depth': 10, 'min_child_sa
mples': 64, 'subsample': 0.6630324394363006, 'colsample_bytree': 0.8
612046108885621, 'reg_alpha': 0.00024293999371271903, 'reg_lambda':
2.9031612313587583}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:   8%|█         | 8/100 [06:49<5
9:39, 38.91s/it]
```

```
[I 2025-09-16 19:31:49,184] Trial 7 finished with value: 0.361915040
29016375 and parameters: {'n_estimators': 1700, 'learning_rate': 0.2
012361561993437, 'num_leaves': 2600, 'max_depth': 4, 'min_child_samp
les': 40, 'subsample': 0.6072502493315309, 'colsample_bytree': 0.632
4543430746492, 'reg_alpha': 3.392702478376279e-05, 'reg_lambda': 1.9
2146529081408e-05}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:   9%|█         | 9/100 [09:57<
2:09:31, 85.40s/it]
```

```
[I 2025-09-16 19:34:56,834] Trial 8 finished with value: 0.351086429
3740711 and parameters: {'n_estimators': 1400, 'learning_rate': 0.05
5182100648122234, 'num_leaves': 1080, 'max_depth': 12, 'min_child_sa
mples': 17, 'subsample': 0.6916475683718059, 'colsample_bytree': 0.9
490331884157979, 'reg_alpha': 5.623357261641144e-06, 'reg_lambda':
3.6319421932283683e-07}. Best is trial 5 with value: 0.4121092274485
245.
```

```
Best trial: 5. Best value: 0.412109:  10%|█         | 10/100 [10:30<
1:44:11, 69.46s/it]
```

```
[I 2025-09-16 19:35:30,584] Trial 9 finished with value: 0.383291548
12963184 and parameters: {'n_estimators': 600, 'learning_rate': 0.02
109622206316228, 'num_leaves': 1360, 'max_depth': 9, 'min_child_samp
les': 41, 'subsample': 0.6199249775114913, 'colsample_bytree': 0.995
7115710175675, 'reg_alpha': 2.7218435595710146e-06, 'reg_lambda': 9.
939883299198569e-07}. Best is trial 5 with value: 0.412109227448524
5.
```

```
Best trial: 5. Best value: 0.412109:  11%|█         | 11/100 [10:35<
1:13:40, 49.67s/it]
```

```
[I 2025-09-16 19:35:35,376] Trial 10 finished with value: 0.36360545
96110653 and parameters: {'n_estimators': 200, 'learning_rate': 0.29
108866027394975, 'num_leaves': 2980, 'max_depth': 6, 'min_child_samp
les': 197, 'subsample': 0.9882372923746179, 'colsample_bytree': 0.74
68899381423617, 'reg_alpha': 0.0351529374480309, 'reg_lambda': 2.362
423068211244e-08}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:  12%|█▏        | 12/100 [11:13<
1:07:47, 46.23s/it]
```

```
[I 2025-09-16 19:36:13,733] Trial 11 finished with value: 0.36060830
80223673 and parameters: {'n_estimators': 500, 'learning_rate': 0.06
738397022772433, 'num_leaves': 1600, 'max_depth': 9, 'min_child_samp
les': 1, 'subsample': 0.7977878305876258, 'colsample_bytree': 0.9774
547966250602, 'reg_alpha': 0.018768615876717912, 'reg_lambda': 0.001
6369743138614195}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:  13%|█▎        | 13/100 [12:09<
1:11:06, 49.04s/it]
```

```
[I 2025-09-16 19:37:09,239] Trial 12 finished with value: 0.36604036
716435917 and parameters: {'n_estimators': 1000, 'learning_rate': 0.
015867487309587845, 'num_leaves': 1740, 'max_depth': 10, 'min_child_
samples': 69, 'subsample': 0.819969589095258, 'colsample_bytree': 0.
9946162198113564, 'reg_alpha': 4.301416805686932e-06, 'reg_lambda':
2.2252956526517787e-06}. Best is trial 5 with value: 0.4121092274485
245.
Best trial: 5. Best value: 0.412109:  14%|█         | 14/100 [12:21<
54:23, 37.94s/it]
[I 2025-09-16 19:37:21,550] Trial 13 finished with value: 0.36368858
82690458 and parameters: {'n_estimators': 200, 'learning_rate': 0.07
88133529027149, 'num_leaves': 1180, 'max_depth': 10, 'min_child_samp
les': 35, 'subsample': 0.9143346727222548, 'colsample_bytree': 0.930
1357475101932, 'reg_alpha': 0.01153993977847027, 'reg_lambda': 4.820
929526426848e-08}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  15%|██        | 15/100 [12:49<
49:20, 34.83s/it]
[I 2025-09-16 19:37:49,159] Trial 14 finished with value: 0.35755501
693282177 and parameters: {'n_estimators': 900, 'learning_rate': 0.0
9683977096747268, 'num_leaves': 2120, 'max_depth': 8, 'min_child_sam
ples': 76, 'subsample': 0.732479182752464, 'colsample_bytree': 0.696
6872256493958, 'reg_alpha': 0.5353372908080501, 'reg_lambda': 8.7985
36616905965e-05}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  16%|██        | 16/100 [13:17<
46:07, 32.95s/it]
[I 2025-09-16 19:38:17,736] Trial 15 finished with value: 0.36262906
63911961 and parameters: {'n_estimators': 500, 'learning_rate': 0.04
2860506746778215, 'num_leaves': 140, 'max_depth': 9, 'min_child_samp
les': 2, 'subsample': 0.7545116366967988, 'colsample_bytree': 0.9216
744034823223, 'reg_alpha': 0.00039050605587832203, 'reg_lambda': 3.8
67146218442792e-06}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  17%|██        | 17/100 [13:21<
33:29, 24.21s/it]
[I 2025-09-16 19:38:21,615] Trial 16 finished with value: 0.35119323
77636088 and parameters: {'n_estimators': 400, 'learning_rate': 0.22
75829856136524, 'num_leaves': 2040, 'max_depth': 3, 'min_child_sampl
es': 50, 'subsample': 0.9176316565176864, 'colsample_bytree': 0.9989
381755496838, 'reg_alpha': 7.539556095216507e-06, 'reg_lambda': 0.02
1139043162138035}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  18%|██        | 18/100 [14:02<
39:44, 29.08s/it]
[I 2025-09-16 19:39:02,031] Trial 17 finished with value: 0.38369224
82932893 and parameters: {'n_estimators': 800, 'learning_rate': 0.01
2908854198869585, 'num_leaves': 1360, 'max_depth': 11, 'min_child_sa
mples': 104, 'subsample': 0.8578372293761874, 'colsample_bytree': 0.
8369135214604657, 'reg_alpha': 9.544742615585499e-07, 'reg_lambda':
1.0294611749906299e-08}. Best is trial 5 with value: 0.4121092274485
245.
Best trial: 5. Best value: 0.412109:  19%|██        | 19/100 [14:57<
49:42, 36.82s/it]
```

```
[I 2025-09-16 19:39:56,901] Trial 18 finished with value: 0.35959157792728685 and parameters: {'n_estimators': 1200, 'learning_rate': 0.10445885007543193, 'num_leaves': 2460, 'max_depth': 11, 'min_child_samples': 111, 'subsample': 0.8778853005552368, 'colsample_bytree': 0.8132041428314108, 'reg_alpha': 1.5501998334466902e-08, 'reg_lambda': 1.530305408577924e-08}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  20%|██        | 20/100 [15:34<49:22, 37.03s/it]
[I 2025-09-16 19:40:34,414] Trial 19 finished with value: 0.3465350326613034 and parameters: {'n_estimators': 900, 'learning_rate': 0.29961666294065104, 'num_leaves': 2920, 'max_depth': 11, 'min_child_samples': 153, 'subsample': 0.990687773218133, 'colsample_bytree': 0.8506185261836758, 'reg_alpha': 0.0031568676621779204, 'reg_lambda': 1.5543990736328513e-07}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  21%|██        | 21/100 [16:29<55:51, 42.42s/it]
[I 2025-09-16 19:41:29,393] Trial 20 finished with value: 0.3620342954742971 and parameters: {'n_estimators': 1100, 'learning_rate': 0.04924691344621008, 'num_leaves': 1700, 'max_depth': 11, 'min_child_samples': 89, 'subsample': 0.8195202815650388, 'colsample_bytree': 0.7168455659841128, 'reg_alpha': 0.1830777501072362, 'reg_lambda': 6.918943177785756e-06}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  22%|██        | 22/100 [17:17<57:09, 43.96s/it]
[I 2025-09-16 19:42:16,962] Trial 21 finished with value: 0.3984658849250766 and parameters: {'n_estimators': 700, 'learning_rate': 0.013121879905356586, 'num_leaves': 1300, 'max_depth': 9, 'min_child_samples': 23, 'subsample': 0.870667366676028, 'colsample_bytree': 0.9669009993072918, 'reg_alpha': 1.0375316209191696e-06, 'reg_lambda': 8.608132645603158e-07}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  23%|██▎       | 23/100 [17:46<50:37, 39.45s/it]
[I 2025-09-16 19:42:45,877] Trial 22 finished with value: 0.40941720847713414 and parameters: {'n_estimators': 800, 'learning_rate': 0.012123626965444114, 'num_leaves': 1380, 'max_depth': 7, 'min_child_samples': 18, 'subsample': 0.8744790044006578, 'colsample_bytree': 0.9530285018483833, 'reg_alpha': 4.291943063229049e-05, 'reg_lambda': 6.373232384369973e-08}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  24%|██▍       | 24/100 [17:57<39:18, 31.03s/it]
[I 2025-09-16 19:42:57,279] Trial 23 finished with value: 0.37508353640796094 and parameters: {'n_estimators': 400, 'learning_rate': 0.04208216942274435, 'num_leaves': 840, 'max_depth': 7, 'min_child_samples': 19, 'subsample': 0.94330304483023, 'colsample_bytree': 0.9498885433443647, 'reg_alpha': 7.399209657081956e-05, 'reg_lambda': 1.4241953499603314e-07}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  25%|██▌       | 25/100 [18:12<32:47, 26.23s/it]
```

```
[I 2025-09-16 19:43:12,304] Trial 24 finished with value: 0.36042167
51447244 and parameters: {'n_estimators': 700, 'learning_rate': 0.07
746009998844973, 'num_leaves': 1420, 'max_depth': 6, 'min_child_samp
les': 19, 'subsample': 0.8928316230626295, 'colsample_bytree': 0.905
6281484029507, 'reg_alpha': 7.196503411147931e-05, 'reg_lambda': 0.0
005413609070414073}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:  26%|███       | 26/100 [18:24<
27:02, 21.93s/it]
```

```
[I 2025-09-16 19:43:24,190] Trial 25 finished with value: 0.39989649
068535044 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
3289476225080805, 'num_leaves': 1880, 'max_depth': 8, 'min_child_sam
ples': 55, 'subsample': 0.8399832368653253, 'colsample_bytree': 0.95
85207203864953, 'reg_alpha': 1.8111627510161498e-05, 'reg_lambda':
8.177103811494526e-08}. Best is trial 5 with value: 0.41210922744852
45.
```

```
Best trial: 5. Best value: 0.412109:  27%|███       | 27/100 [18:33<
22:04, 18.15s/it]
```

```
[I 2025-09-16 19:43:33,523] Trial 26 finished with value: 0.39456474
03934941 and parameters: {'n_estimators': 300, 'learning_rate': 0.03
743872200280045, 'num_leaves': 2240, 'max_depth': 7, 'min_child_samp
les': 56, 'subsample': 0.7820181191958346, 'colsample_bytree': 0.891
5595249073704, 'reg_alpha': 0.0026722800998810778, 'reg_lambda': 7.4
46802492575329e-08}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:  28%|███       | 28/100 [18:42<
18:22, 15.31s/it]
```

```
[I 2025-09-16 19:43:42,218] Trial 27 finished with value: 0.35716740
36302707 and parameters: {'n_estimators': 400, 'learning_rate': 0.09
197257759399037, 'num_leaves': 2320, 'max_depth': 6, 'min_child_samp
les': 81, 'subsample': 0.8411874361117087, 'colsample_bytree': 0.936
4553165729664, 'reg_alpha': 2.2711958899228182e-05, 'reg_lambda': 5.
919690106307948e-06}. Best is trial 5 with value: 0.412109227448524
5.
```

```
Best trial: 5. Best value: 0.412109:  29%|███       | 29/100 [19:02<
19:52, 16.80s/it]
```

```
[I 2025-09-16 19:44:02,497] Trial 28 finished with value: 0.36658803
97166653 and parameters: {'n_estimators': 500, 'learning_rate': 0.12
232557663764791, 'num_leaves': 1740, 'max_depth': 8, 'min_child_samp
les': 27, 'subsample': 0.9425456669440123, 'colsample_bytree': 0.962
94680760785, 'reg_alpha': 0.00041114302133120166, 'reg_lambda': 1.88
60067696139113e-07}. Best is trial 5 with value: 0.4121092274485245.
```

```
Best trial: 5. Best value: 0.412109:  30%|███       | 30/100 [19:29<
23:02, 19.75s/it]
```

```
[I 2025-09-16 19:44:29,125] Trial 29 finished with value: 0.35125935
60000356 and parameters: {'n_estimators': 1900, 'learning_rate': 0.2
591866514123859, 'num_leaves': 1900, 'max_depth': 5, 'min_child_samp
les': 54, 'subsample': 0.7668184892882802, 'colsample_bytree': 0.913
8799705681674, 'reg_alpha': 0.00013457604885019992, 'reg_lambda': 6.
413455679231049e-07}. Best is trial 5 with value: 0.412109227448524
5.
```

```
Best trial: 5. Best value: 0.412109:  31%|███       | 31/100 [19:46<
21:45, 18.92s/it]
```

```
[I 2025-09-16 19:44:46,121] Trial 30 finished with value: 0.36524400
808837376 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
6258549189602126, 'num_leaves': 2700, 'max_depth': 8, 'min_child_sam
ples': 7, 'subsample': 0.828915341224647, 'colsample_bytree': 0.8873
234871694902, 'reg_alpha': 0.001093196353584572, 'reg_lambda': 7.486
563040505412e-05}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 5. Best value: 0.412109:  32%|███▏      | 32/100 [20:20<
26:31, 23.40s/it]
[I 2025-09-16 19:45:19,973] Trial 31 finished with value: 0.36432944
60666427 and parameters: {'n_estimators': 600, 'learning_rate': 0.03
5066195872967026, 'num_leaves': 1160, 'max_depth': 9, 'min_child_sam
ples': 29, 'subsample': 0.9036177766976802, 'colsample_bytree': 0.96
55595414052965, 'reg_alpha': 5.940103877059974e-07, 'reg_lambda': 6.
458780387990196e-07}. Best is trial 5 with value: 0.412109227448524
5.
Best trial: 5. Best value: 0.412109:  33%|███▎      | 33/100 [21:03<
32:44, 29.32s/it]
[I 2025-09-16 19:46:03,086] Trial 32 finished with value: 0.38931514
76612597 and parameters: {'n_estimators': 800, 'learning_rate': 0.01
3053579132003777, 'num_leaves': 940, 'max_depth': 10, 'min_child_sam
ples': 43, 'subsample': 0.8594317383872057, 'colsample_bytree': 0.96
94805073766566, 'reg_alpha': 1.5245519011476914e-05, 'reg_lambda':
5.495625050383217e-08}. Best is trial 5 with value: 0.41210922744852
45.
Best trial: 5. Best value: 0.412109:  34%|███▍      | 34/100 [21:24<
29:38, 26.94s/it]
[I 2025-09-16 19:46:24,483] Trial 33 finished with value: 0.37380693
67344258 and parameters: {'n_estimators': 600, 'learning_rate': 0.02
6466050978555682, 'num_leaves': 1520, 'max_depth': 7, 'min_child_sam
ples': 20, 'subsample': 0.8822578932909992, 'colsample_bytree': 0.78
64054803147651, 'reg_alpha': 3.928255679616104e-07, 'reg_lambda': 1.
4222950904213736e-06}. Best is trial 5 with value: 0.412109227448524
5.
Best trial: 5. Best value: 0.412109:  35%|███▌      | 35/100 [22:16<
37:07, 34.28s/it]
[I 2025-09-16 19:47:15,872] Trial 34 finished with value: 0.36126696
66215623 and parameters: {'n_estimators': 800, 'learning_rate': 0.05
87246919994335, 'num_leaves': 640, 'max_depth': 9, 'min_child_sample
s': 9, 'subsample': 0.9399575681778802, 'colsample_bytree': 0.939151
6056492365, 'reg_alpha': 7.965157723297435e-08, 'reg_lambda': 2.5196
243856316435e-07}. Best is trial 5 with value: 0.4121092274485245.
Best trial: 35. Best value: 0.416317:  36%|███▌      | 36/100 [22:48
<35:51, 33.61s/it]
[I 2025-09-16 19:47:47,944] Trial 35 finished with value: 0.41631696
43227246 and parameters: {'n_estimators': 700, 'learning_rate': 0.01
0922620353229384, 'num_leaves': 1840, 'max_depth': 8, 'min_child_sam
ples': 31, 'subsample': 0.8436538590401458, 'colsample_bytree': 0.91
26461493354505, 'reg_alpha': 1.8253534118332354e-06, 'reg_lambda':
1.2415144252500045e-05}. Best is trial 35 with value: 0.416316964322
7246.
Best trial: 35. Best value: 0.416317:  37%|███▋      | 37/100 [23:11
<32:00, 30.49s/it]
```

```
[I 2025-09-16 19:48:11,149] Trial 36 finished with value: 0.35447321
26652196 and parameters: {'n_estimators': 1200, 'learning_rate': 0.0
3480826118539909, 'num_leaves': 1840, 'max_depth': 6, 'min_child_sam
ples': 54, 'subsample': 0.8015501634593413, 'colsample_bytree': 0.86
83901860520471, 'reg_alpha': 1.640965420351391e-07, 'reg_lambda': 0.
00022712900194809936}. Best is trial 35 with value: 0.41631696432272
46.
```

```
Best trial: 35. Best value: 0.416317:  38%|████      | 38/100 [23:26
<26:42, 25.85s/it]
```

```
[I 2025-09-16 19:48:26,170] Trial 37 finished with value: 0.36428619
56568962 and parameters: {'n_estimators': 1000, 'learning_rate': 0.1
2102160762842244, 'num_leaves': 1960, 'max_depth': 5, 'min_child_sam
ples': 32, 'subsample': 0.8448855371370235, 'colsample_bytree': 0.91
99221846609718, 'reg_alpha': 1.9244659400468994e-06, 'reg_lambda':
3.21772699993786e-05}. Best is trial 35 with value: 0.41631696432272
46.
```

```
Best trial: 35. Best value: 0.416317:  39%|████      | 39/100 [23:39
<22:26, 22.08s/it]
```

```
[I 2025-09-16 19:48:39,450] Trial 38 finished with value: 0.35257306
47111173 and parameters: {'n_estimators': 300, 'learning_rate': 0.07
778429630952706, 'num_leaves': 2800, 'max_depth': 8, 'min_child_samp
les': 64, 'subsample': 0.7306181084909973, 'colsample_bytree': 0.616
8660225060861, 'reg_alpha': 3.290543310133538e-05, 'reg_lambda': 1.0
234795204930784e-05}. Best is trial 35 with value: 0.416316964322724
6.
```

```
Best trial: 35. Best value: 0.416317:  40%|████      | 40/100 [23:49
<18:26, 18.43s/it]
```

```
[I 2025-09-16 19:48:49,381] Trial 39 finished with value: 0.35436661
95613911 and parameters: {'n_estimators': 600, 'learning_rate': 0.19
83372447069625, 'num_leaves': 2380, 'max_depth': 7, 'min_child_sampl
es': 44, 'subsample': 0.8091138406378349, 'colsample_bytree': 0.8426
244772800021, 'reg_alpha': 3.820443286589636, 'reg_lambda': 1.556684
149200794e-05}. Best is trial 35 with value: 0.4163169643227246.
```

```
Best trial: 35. Best value: 0.416317:  41%|████      | 41/100 [24:29
<24:36, 25.03s/it]
```

```
[I 2025-09-16 19:49:29,807] Trial 40 finished with value: 0.35908848
493956436 and parameters: {'n_estimators': 900, 'learning_rate': 0.0
28808324316034382, 'num_leaves': 1580, 'max_depth': 8, 'min_child_sa
mples': 12, 'subsample': 0.8422030217420952, 'colsample_bytree': 0.8
837390347571612, 'reg_alpha': 8.55783569543193e-06, 'reg_lambda': 0.
004770348648452390 5}. Best is trial 35 with value: 0.416316964322724
6.
```

```
Best trial: 35. Best value: 0.416317:  42%|████▏     | 42/100 [25:12
<29:22, 30.39s/it]
```

```
[I 2025-09-16 19:50:12,697] Trial 41 finished with value: 0.39611086
05285234 and parameters: {'n_estimators': 700, 'learning_rate': 0.01
4179849479514214, 'num_leaves': 1220, 'max_depth': 9, 'min_child_sam
ples': 26, 'subsample': 0.8685543221098221, 'colsample_bytree': 0.97
81128455239041, 'reg_alpha': 1.523262630249935 6e-06, 'reg_lambda':
1.5916966882473986e-06}. Best is trial 35 with value: 0.416316964322
7246.
```

```
Best trial: 35. Best value: 0.416317:  43%|████▎     | 43/100 [25:51
<31:18, 32.96s/it]
```

```
[I 2025-09-16 19:50:51,666] Trial 42 finished with value: 0.36303202476483054 and parameters: {'n_estimators': 700, 'learning_rate': 0.026964161983255453, 'num_leaves': 1000, 'max_depth': 10, 'min_child_samples': 36, 'subsample': 0.894212215983288, 'colsample_bytree': 0.9512798542563786, 'reg_alpha': 1.9721114564915374e-07, 'reg_lambda': 3.172732989807236e-08}. Best is trial 35 with value: 0.4163169643227246.
```

```
Best trial: 35. Best value: 0.416317:  44%|████      | 44/100 [26:10<26:42, 28.62s/it]
```

```
[I 2025-09-16 19:51:10,149] Trial 43 finished with value: 0.3621880135988295 and parameters: {'n_estimators': 500, 'learning_rate': 0.052003292408821546, 'num_leaves': 780, 'max_depth': 8, 'min_child_samples': 13, 'subsample': 0.7878478945914723, 'colsample_bytree': 0.9826719086225374, 'reg_alpha': 0.001017732892790625, 'reg_lambda': 3.235694460178078e-07}. Best is trial 35 with value: 0.4163169643227246.
```

```
Best trial: 44. Best value: 0.416382:  45%|████      | 45/100 [26:54<30:25, 33.19s/it]
```

```
[I 2025-09-16 19:51:54,009] Trial 44 finished with value: 0.41638235155918635 and parameters: {'n_estimators': 600, 'learning_rate': 0.01151534000197272, 'num_leaves': 1380, 'max_depth': 9, 'min_child_samples': 23, 'subsample': 0.9200449899978195, 'colsample_bytree': 0.9071335474322357, 'reg_alpha': 3.333142584838301e-08, 'reg_lambda': 2.3421365142395054e-06}. Best is trial 44 with value: 0.41638235155918635.
```

```
Best trial: 45. Best value: 0.445643:  46%|████      | 46/100 [27:14<26:15, 29.18s/it]
```

```
[I 2025-09-16 19:52:13,820] Trial 45 finished with value: 0.4456428160508864 and parameters: {'n_estimators': 200, 'learning_rate': 0.01032565119154107, 'num_leaves': 1440, 'max_depth': 10, 'min_child_samples': 45, 'subsample': 0.9643946012301383, 'colsample_bytree': 0.8979866059177901, 'reg_alpha': 1.2879201869482782e-08, 'reg_lambda': 2.74426603318653e-06}. Best is trial 45 with value: 0.4456428160508864.
```

```
Best trial: 45. Best value: 0.445643:  47%|████      | 47/100 [27:26<21:27, 24.29s/it]
```

```
[I 2025-09-16 19:52:26,693] Trial 46 finished with value: 0.3589598039527624 and parameters: {'n_estimators': 200, 'learning_rate': 0.14088850486863339, 'num_leaves': 340, 'max_depth': 10, 'min_child_samples': 43, 'subsample': 0.9550719863841772, 'colsample_bytree': 0.9021005377909379, 'reg_alpha': 3.12652153512344e-08, 'reg_lambda': 3.542052698932386e-06}. Best is trial 45 with value: 0.4456428160508864.
```

```
Best trial: 45. Best value: 0.445643:  48%|████      | 48/100 [27:44<19:18, 22.28s/it]
```

```
[I 2025-09-16 19:52:44,294] Trial 47 finished with value: 0.4374964998499592 and parameters: {'n_estimators': 400, 'learning_rate': 0.010273167782226414, 'num_leaves': 1080, 'max_depth': 10, 'min_child_samples': 193, 'subsample': 0.9224434212549512, 'colsample_bytree': 0.8638055822177025, 'reg_alpha': 1.0217095784864622e-08, 'reg_lambda': 5.936867345954422e-05}. Best is trial 45 with value: 0.4456428160508864.
```

```
Best trial: 45. Best value: 0.445643:  49%|████      | 49/100 [28:03<18:07, 21.33s/it]
```

```
[I 2025-09-16 19:53:03,409] Trial 48 finished with value: 0.36603840
597390186 and parameters: {'n_estimators': 400, 'learning_rate': 0.0
6673860556784296, 'num_leaves': 680, 'max_depth': 12, 'min_child_sam
ples': 131, 'subsample': 0.9660668211838489, 'colsample_bytree': 0.8
25498788683074, 'reg_alpha': 5.451820288560502e-08, 'reg_lambda': 7.
368247319134005e-05}. Best is trial 45 with value: 0.445642816050886
4.
Best trial: 45. Best value: 0.445643:  50%|█████     | 50/100 [28:14
<15:12, 18.26s/it]
[I 2025-09-16 19:53:14,496] Trial 49 finished with value: 0.38800748
732169266 and parameters: {'n_estimators': 200, 'learning_rate': 0.0
5201844121796027, 'num_leaves': 1040, 'max_depth': 11, 'min_child_sa
mples': 177, 'subsample': 0.9736655581817201, 'colsample_bytree': 0.
8674488967100211, 'reg_alpha': 1.0304710475706565e-08, 'reg_lambda':
0.00020191470646301589}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  51%|█████     | 51/100 [28:30
<14:14, 17.44s/it]
[I 2025-09-16 19:53:30,026] Trial 50 finished with value: 0.39730128
87844326 and parameters: {'n_estimators': 400, 'learning_rate': 0.02
3325421592354206, 'num_leaves': 400, 'max_depth': 10, 'min_child_sam
ples': 147, 'subsample': 0.9233686703513633, 'colsample_bytree': 0.8
548075695933921, 'reg_alpha': 2.6515516983063032e-08, 'reg_lambda':
3.017114951853825e-05}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  52%|█████▏    | 52/100 [28:46
<13:46, 17.23s/it]
[I 2025-09-16 19:53:46,760] Trial 51 finished with value: 0.42519715
707705236 and parameters: {'n_estimators': 500, 'learning_rate': 0.0
13131084543896759, 'num_leaves': 1460, 'max_depth': 9, 'min_child_sa
mples': 200, 'subsample': 0.9266778842717938, 'colsample_bytree': 0.
9307348691612022, 'reg_alpha': 5.665155604002903e-08, 'reg_lambda':
3.4340037527239067e-06}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  53%|█████▎    | 53/100 [29:03
<13:25, 17.14s/it]
[I 2025-09-16 19:54:03,688] Trial 52 finished with value: 0.36895951
32180502 and parameters: {'n_estimators': 500, 'learning_rate': 0.04
418556215233112, 'num_leaves': 1480, 'max_depth': 9, 'min_child_samp
les': 200, 'subsample': 0.925828423533696, 'colsample_bytree': 0.927
6320515488281, 'reg_alpha': 9.362622607005927e-08, 'reg_lambda': 1.2
373600844542316e-05}. Best is trial 45 with value: 0.445642816050886
4.
Best trial: 45. Best value: 0.445643:  54%|█████▍    | 54/100 [29:27
<14:44, 19.23s/it]
[I 2025-09-16 19:54:27,795] Trial 53 finished with value: 0.37417254
32547344 and parameters: {'n_estimators': 600, 'learning_rate': 0.02
4711579671474734, 'num_leaves': 1680, 'max_depth': 10, 'min_child_sa
mples': 187, 'subsample': 0.971520933177052, 'colsample_bytree': 0.9
041603346680775, 'reg_alpha': 2.6754173947923973e-08, 'reg_lambda':
2.924945438537944e-06}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  55%|█████▌    | 55/100 [29:42
<13:24, 17.87s/it]
```

```
[I 2025-09-16 19:54:42,496] Trial 54 finished with value: 0.41469899
29612392 and parameters: {'n_estimators': 300, 'learning_rate': 0.02
3804367018645294, 'num_leaves': 1140, 'max_depth': 11, 'min_child_sa
mples': 172, 'subsample': 0.9997850139790635, 'colsample_bytree': 0.
8787101687105329, 'reg_alpha': 1.2765610936912726e-08, 'reg_lambda':
6.302908370661877e-06}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  56%|█████▌    | 56/100 [29:59
<12:47, 17.45s/it]
[I 2025-09-16 19:54:58,972] Trial 55 finished with value: 0.41223197
49042423 and parameters: {'n_estimators': 300, 'learning_rate': 0.02
2958199544141293, 'num_leaves': 1240, 'max_depth': 12, 'min_child_sa
mples': 190, 'subsample': 0.9977850339411198, 'colsample_bytree': 0.
8789029111790037, 'reg_alpha': 1.2378968560022888e-08, 'reg_lambda':
0.0005350953895494973}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  57%|█████▋    | 57/100 [30:09
<11:03, 15.42s/it]
[I 2025-09-16 19:55:09,644] Trial 56 finished with value: 0.36490842
20118168 and parameters: {'n_estimators': 200, 'learning_rate': 0.18
523986067508208, 'num_leaves': 1120, 'max_depth': 11, 'min_child_sam
ples': 161, 'subsample': 0.9812743676897894, 'colsample_bytree': 0.7
954220319172175, 'reg_alpha': 3.11201280818812e-07, 'reg_lambda': 0.
3009313207010845}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  58%|█████▊    | 58/100 [30:24
<10:42, 15.30s/it]
[I 2025-09-16 19:55:24,659] Trial 57 finished with value: 0.37108151
4922782 and parameters: {'n_estimators': 400, 'learning_rate': 0.042
885087627944934, 'num_leaves': 1620, 'max_depth': 9, 'min_child_samp
les': 175, 'subsample': 0.9340304140362023, 'colsample_bytree': 0.82
48392486718221, 'reg_alpha': 5.70779978355132e-08, 'reg_lambda': 3.7
33113424025625e-05}. Best is trial 45 with value: 0.445642816050886
4.
Best trial: 45. Best value: 0.445643:  59%|█████▉    | 59/100 [30:38
<10:06, 14.80s/it]
[I 2025-09-16 19:55:38,299] Trial 58 finished with value: 0.43092014
61265288 and parameters: {'n_estimators': 300, 'learning_rate': 0.01
5906671594043686, 'num_leaves': 1340, 'max_depth': 10, 'min_child_sa
mples': 180, 'subsample': 0.9582389535666741, 'colsample_bytree': 0.
9143912413102988, 'reg_alpha': 2.1971589739891966e-08, 'reg_lambda':
5.500033691829783e-06}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  60%|██████    | 60/100 [30:58
<10:55, 16.39s/it]
[I 2025-09-16 19:55:58,413] Trial 59 finished with value: 0.36854530
677626857 and parameters: {'n_estimators': 500, 'learning_rate': 0.0
3662735667204686, 'num_leaves': 1300, 'max_depth': 10, 'min_child_sa
mples': 187, 'subsample': 0.9576482208822169, 'colsample_bytree': 0.
9198686440300247, 'reg_alpha': 1.2729570725429951e-07, 'reg_lambda':
0.00013596597658247335}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  61%|██████    | 61/100 [31:17
<11:06, 17.10s/it]
```

```
[I 2025-09-16 19:56:17,155] Trial 60 finished with value: 0.42475182219351415 and parameters: {'n_estimators': 400, 'learning_rate': 0.01391332923359847, 'num_leaves': 1480, 'max_depth': 9, 'min_child_samples': 114, 'subsample': 0.9115437995260084, 'colsample_bytree': 0.8973353687781068, 'reg_alpha': 3.4847373797053726e-08, 'reg_lambda': 2.27525405073396e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  62%|██████▏   | 62/100 [31:37<11:19, 17.88s/it]
[I 2025-09-16 19:56:36,862] Trial 61 finished with value: 0.4363276213241737 and parameters: {'n_estimators': 400, 'learning_rate': 0.010497938754690845, 'num_leaves': 1460, 'max_depth': 9, 'min_child_samples': 116, 'subsample': 0.9093328822931985, 'colsample_bytree': 0.9071726805011517, 'reg_alpha': 2.609089959062996e-08, 'reg_lambda': 2.2083030978235013e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  63%|██████▎   | 63/100 [31:54<11:01, 17.89s/it]
[I 2025-09-16 19:56:54,758] Trial 62 finished with value: 0.41034288977674127 and parameters: {'n_estimators': 400, 'learning_rate': 0.020000309647714192, 'num_leaves': 1500, 'max_depth': 9, 'min_child_samples': 118, 'subsample': 0.9082303264170464, 'colsample_bytree': 0.895332346709145, 'reg_alpha': 2.589484911113836e-08, 'reg_lambda': 2.1592251505324034e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  64%|██████▍   | 64/100 [32:07<09:48, 16.35s/it]
[I 2025-09-16 19:57:07,538] Trial 63 finished with value: 0.4383309543218621 and parameters: {'n_estimators': 200, 'learning_rate': 0.012364520840926704, 'num_leaves': 1400, 'max_depth': 10, 'min_child_samples': 99, 'subsample': 0.9505669589253049, 'colsample_bytree': 0.9342373356334188, 'reg_alpha': 4.951919129156279e-08, 'reg_lambda': 8.71298033287047e-07}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  65%|██████▌   | 65/100 [32:18<08:31, 14.61s/it]
[I 2025-09-16 19:57:18,088] Trial 64 finished with value: 0.3948445613688205 and parameters: {'n_estimators': 200, 'learning_rate': 0.048021968462927105, 'num_leaves': 1300, 'max_depth': 10, 'min_child_samples': 93, 'subsample': 0.9540229482678396, 'colsample_bytree': 0.938208147141056, 'reg_alpha': 7.027778877304512e-08, 'reg_lambda': 9.317188647335681e-07}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  66%|██████▌   | 66/100 [32:31<08:03, 14.21s/it]
[I 2025-09-16 19:57:31,354] Trial 65 finished with value: 0.39314541870725733 and parameters: {'n_estimators': 300, 'learning_rate': 0.0304989657423781, 'num_leaves': 1480, 'max_depth': 10, 'min_child_samples': 105, 'subsample': 0.8913683377895142, 'colsample_bytree': 0.8574386607844644, 'reg_alpha': 5.605848247054003e-07, 'reg_lambda': 5.149886756983365e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  67%|██████▋   | 67/100 [32:42<07:18, 13.29s/it]
```

```
[I 2025-09-16 19:57:42,514] Trial 66 finished with value: 0.43166498
09112942 and parameters: {'n_estimators': 200, 'learning_rate': 0.01
8966080135371273, 'num_leaves': 1600, 'max_depth': 11, 'min_child_sa
mples': 142, 'subsample': 0.9337069855863858, 'colsample_bytree': 0.
6684205646373738, 'reg_alpha': 2.0602475134862892e-08, 'reg_lambda':
3.864919529641128e-07}. Best is trial 45 with value: 0.4456428160508
864.
```

```
Best trial: 45. Best value: 0.445643:  68%|███████   | 68/100 [32:51
<06:25, 12.05s/it]
```

```
[I 2025-09-16 19:57:51,658] Trial 67 finished with value: 0.36119828
751856486 and parameters: {'n_estimators': 200, 'learning_rate': 0.2
3207894003185467, 'num_leaves': 1640, 'max_depth': 11, 'min_child_sa
mples': 141, 'subsample': 0.931386498163471, 'colsample_bytree': 0.6
747824423873824, 'reg_alpha': 2.0460846222826612e-07, 'reg_lambda':
6.594088038546273e-07}. Best is trial 45 with value: 0.4456428160508
864.
```

```
Best trial: 45. Best value: 0.445643:  69%|███████   | 69/100 [33:02
<06:02, 11.69s/it]
```

```
[I 2025-09-16 19:58:02,496] Trial 68 finished with value: 0.36629296
53980631 and parameters: {'n_estimators': 300, 'learning_rate': 0.06
996800029402037, 'num_leaves': 900, 'max_depth': 11, 'min_child_samp
les': 160, 'subsample': 0.9841121882794341, 'colsample_bytree': 0.71
80319882390684, 'reg_alpha': 1.890902135657893e-08, 'reg_lambda': 2.
9205796469399395e-07}. Best is trial 45 with value: 0.44564281605088
64.
```

```
Best trial: 45. Best value: 0.445643:  70%|███████   | 70/100 [33:10
<05:11, 10.40s/it]
```

```
[I 2025-09-16 19:58:09,883] Trial 69 finished with value: 0.37887656
70533967 and parameters: {'n_estimators': 200, 'learning_rate': 0.05
709454965335935, 'num_leaves': 1760, 'max_depth': 10, 'min_child_sam
ples': 193, 'subsample': 0.9504026513126937, 'colsample_bytree': 0.6
547486916338716, 'reg_alpha': 1.0448096133025093e-08, 'reg_lambda':
1.2120962938205184e-07}. Best is trial 45 with value: 0.445642816050
8864.
```

```
Best trial: 45. Best value: 0.445643:  71%|███████   | 71/100 [33:22
<05:15, 10.87s/it]
```

```
[I 2025-09-16 19:58:21,867] Trial 70 finished with value: 0.37847221
149150534 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
3682059926704963, 'num_leaves': 1260, 'max_depth': 10, 'min_child_sa
mples': 128, 'subsample': 0.9709640905506762, 'colsample_bytree': 0.
773361041580188, 'reg_alpha': 1.1757886392664587e-07, 'reg_lambda':
2.0566913878561594e-05}. Best is trial 45 with value: 0.445642816050
8864.
```

```
Best trial: 45. Best value: 0.445643:  72%|███████   | 72/100 [33:44
<06:41, 14.32s/it]
```

```
[I 2025-09-16 19:58:44,238] Trial 71 finished with value: 0.39133559
74882452 and parameters: {'n_estimators': 400, 'learning_rate': 0.01
9900221137541883, 'num_leaves': 1420, 'max_depth': 12, 'min_child_sa
mples': 114, 'subsample': 0.9068859131183066, 'colsample_bytree': 0.
7501541337489087, 'reg_alpha': 5.027412936622993e-08, 'reg_lambda':
1.153558829806766e-06}. Best is trial 45 with value: 0.4456428160508
864.
```

```
Best trial: 45. Best value: 0.445643:  73%|███████   | 73/100 [34:02
<06:53, 15.32s/it]
```

```
[I 2025-09-16 19:59:01,893] Trial 72 finished with value: 0.42763551896048274 and parameters: {'n_estimators': 500, 'learning_rate': 0.010999627969497251, 'num_leaves': 1520, 'max_depth': 9, 'min_child_samples': 120, 'subsample': 0.9441364464294665, 'colsample_bytree': 0.8942089602764192, 'reg_alpha': 4.6111740975620926e-08, 'reg_lambda': 4.110636117092207e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  74%|███████▍  | 74/100 [35:13<13:57, 32.22s/it]
[I 2025-09-16 20:00:13,544] Trial 73 finished with value: 0.3665263140116825 and parameters: {'n_estimators': 1700, 'learning_rate': 0.01897267718692927, 'num_leaves': 1040, 'max_depth': 11, 'min_child_samples': 122, 'subsample': 0.9398899932529243, 'colsample_bytree': 0.9327810191512703, 'reg_alpha': 1.9129059033688242e-08, 'reg_lambda': 7.657675526523476e-06}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  75%|███████▌  | 75/100 [35:30<11:33, 27.73s/it]
[I 2025-09-16 20:00:30,791] Trial 74 finished with value: 0.37504084546435246 and parameters: {'n_estimators': 500, 'learning_rate': 0.03139725606775483, 'num_leaves': 1800, 'max_depth': 10, 'min_child_samples': 181, 'subsample': 0.9605247951568613, 'colsample_bytree': 0.9238917672710945, 'reg_alpha': 8.47314855832285e-08, 'reg_lambda': 3.804004641203323e-07}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  76%|███████▌  | 76/100 [35:40<08:55, 22.29s/it]
[I 2025-09-16 20:00:40,401] Trial 75 finished with value: 0.4410570010561857 and parameters: {'n_estimators': 200, 'learning_rate': 0.010628226333112384, 'num_leaves': 1540, 'max_depth': 9, 'min_child_samples': 137, 'subsample': 0.9473780756142076, 'colsample_bytree': 0.9427283363815416, 'reg_alpha': 3.1079527823852816e-07, 'reg_lambda': 4.8658757660147716e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  77%|███████▋  | 77/100 [35:50<07:04, 18.44s/it]
[I 2025-09-16 20:00:49,866] Trial 76 finished with value: 0.40303277133272486 and parameters: {'n_estimators': 200, 'learning_rate': 0.041491346310592515, 'num_leaves': 1540, 'max_depth': 11, 'min_child_samples': 144, 'subsample': 0.947022595568163, 'colsample_bytree': 0.9118900716456941, 'reg_alpha': 4.0026314252847e-07, 'reg_lambda': 0.0015679932602530725}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  78%|███████▊  | 78/100 [35:58<05:42, 15.58s/it]
[I 2025-09-16 20:00:58,767] Trial 77 finished with value: 0.4246975885447009 and parameters: {'n_estimators': 200, 'learning_rate': 0.029221035271597022, 'num_leaves': 1580, 'max_depth': 10, 'min_child_samples': 134, 'subsample': 0.9802384786179965, 'colsample_bytree': 0.9453339103916208, 'reg_alpha': 2.0998530945650254e-08, 'reg_lambda': 5.6830502195644576e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  79%|███████▉  | 79/100 [36:02<04:09, 11.86s/it]
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[I 2025-09-16 20:01:01,943] Trial 78 finished with value: 0.41254187
7718545 and parameters: {'n_estimators': 300, 'learning_rate': 0.018
739935902616266, 'num_leaves': 1340, 'max_depth': 3, 'min_child_samp
les': 104, 'subsample': 0.8984561521479932, 'colsample_bytree': 0.83
78078225377654, 'reg_alpha': 1.4639812966875327e-07, 'reg_lambda':
0.0006073100673251433}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  80%|████████  | 80/100 [36:18
<04:23, 13.17s/it]
[I 2025-09-16 20:01:18,174] Trial 79 finished with value: 0.43772147
41092875 and parameters: {'n_estimators': 300, 'learning_rate': 0.01
0176446306147125, 'num_leaves': 1680, 'max_depth': 9, 'min_child_sam
ples': 83, 'subsample': 0.6510908429046822, 'colsample_bytree': 0.88
89172522432235, 'reg_alpha': 2.372470392721866e-07, 'reg_lambda': 2.
2732574299525218e-05}. Best is trial 45 with value: 0.44564281605088
64.
Best trial: 45. Best value: 0.445643:  81%|████████  | 81/100 [36:31
<04:08, 13.07s/it]
[I 2025-09-16 20:01:31,008] Trial 80 finished with value: 0.37240442
385135897 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
47992051818622206, 'num_leaves': 2060, 'max_depth': 9, 'min_child_sa
mples': 82, 'subsample': 0.6458664574398665, 'colsample_bytree': 0.8
697015969241046, 'reg_alpha': 9.12213151409308e-07, 'reg_lambda': 2.
627377784770901e-05}. Best is trial 45 with value: 0.445642816050886
4.
Best trial: 45. Best value: 0.445643:  82%|████████▏ | 82/100 [36:41
<03:40, 12.23s/it]
[I 2025-09-16 20:01:41,275] Trial 81 finished with value: 0.43448488
372908445 and parameters: {'n_estimators': 200, 'learning_rate': 0.0
18952495358620886, 'num_leaves': 1960, 'max_depth': 9, 'min_child_sa
mples': 93, 'subsample': 0.6630406916047108, 'colsample_bytree': 0.8
870534778309681, 'reg_alpha': 2.1462600016699822e-07, 'reg_lambda':
0.00011285501279140224}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  83%|████████▎ | 83/100 [36:55
<03:37, 12.79s/it]
[I 2025-09-16 20:01:55,366] Trial 82 finished with value: 0.44436463
174469887 and parameters: {'n_estimators': 200, 'learning_rate': 0.0
10190358493243469, 'num_leaves': 1960, 'max_depth': 10, 'min_child_s
amples': 97, 'subsample': 0.6775158907286002, 'colsample_bytree': 0.
8870796700369746, 'reg_alpha': 3.004152332271235e-07, 'reg_lambda':
4.427046792877967e-05}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  84%|████████▍ | 84/100 [37:05
<03:11, 11.95s/it]
[I 2025-09-16 20:02:05,368] Trial 83 finished with value: 0.42098383
132665906 and parameters: {'n_estimators': 200, 'learning_rate': 0.0
320923293290911 1, 'num_leaves': 2200, 'max_depth': 9, 'min_child_sam
ples': 96, 'subsample': 0.6750457618285315, 'colsample_bytree': 0.84
84404005114992, 'reg_alpha': 3.5089518594127284e-06, 'reg_lambda':
0.00013022767000461544}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  85%|████████▌ | 85/100 [37:14
<02:45, 11.04s/it]
```

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[I 2025-09-16 20:02:14,283] Trial 84 finished with value: 0.42885923842314677 and parameters: {'n_estimators': 200, 'learning_rate': 0.023657924174409203, 'num_leaves': 2160, 'max_depth': 8, 'min_child_samples': 73, 'subsample': 0.627352246913619, 'colsample_bytree': 0.8870614120143491, 'reg_alpha': 2.828206976745004e-07, 'reg_lambda': 5.573502527535592e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  86%|████████▌ | 86/100 [37:26<02:37, 11.26s/it]
[I 2025-09-16 20:02:26,060] Trial 85 finished with value: 0.4409432921781066 and parameters: {'n_estimators': 200, 'learning_rate': 0.010010798471558386, 'num_leaves': 1960, 'max_depth': 9, 'min_child_samples': 87, 'subsample': 0.6609399233215402, 'colsample_bytree': 0.8156809736133094, 'reg_alpha': 7.387237692535511e-07, 'reg_lambda': 0.00012642553463976998}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  87%|████████▋ | 87/100 [37:42<02:47, 12.90s/it]
[I 2025-09-16 20:02:42,779] Trial 86 finished with value: 0.3628178313486313 and parameters: {'n_estimators': 400, 'learning_rate': 0.04091553526655671, 'num_leaves': 2000, 'max_depth': 9, 'min_child_samples': 85, 'subsample': 0.6603496449617923, 'colsample_bytree': 0.8078623209890812, 'reg_alpha': 6.648399585584143e-07, 'reg_lambda': 0.00030549946749071485}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  88%|████████▊ | 88/100 [37:52<02:23, 11.92s/it]
[I 2025-09-16 20:02:52,417] Trial 87 finished with value: 0.35599680054376465 and parameters: {'n_estimators': 300, 'learning_rate': 0.1323276342588593, 'num_leaves': 2060, 'max_depth': 8, 'min_child_samples': 100, 'subsample': 0.7080500515199643, 'colsample_bytree': 0.8604451521345848, 'reg_alpha': 1.256997490871801e-06, 'reg_lambda': 0.0007739703099768394}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  89%|████████▉ | 89/100 [38:04<02:09, 11.77s/it]
[I 2025-09-16 20:03:03,834] Trial 88 finished with value: 0.4404080228745525 and parameters: {'n_estimators': 200, 'learning_rate': 0.01049455483656122, 'num_leaves': 1940, 'max_depth': 9, 'min_child_samples': 88, 'subsample': 0.6838738086987166, 'colsample_bytree': 0.8700949305439546, 'reg_alpha': 2.1584585432335293e-07, 'reg_lambda': 9.209230170744752e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  90%|█████████ | 90/100 [38:19<02:08, 12.82s/it]
[I 2025-09-16 20:03:19,107] Trial 89 finished with value: 0.3649449218087083 and parameters: {'n_estimators': 300, 'learning_rate': 0.16011605564362702, 'num_leaves': 1900, 'max_depth': 10, 'min_child_samples': 64, 'subsample': 0.6933587271441649, 'colsample_bytree': 0.8456481106580656, 'reg_alpha': 4.550082981122551e-07, 'reg_lambda': 0.0035807932646705143}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  91%|█████████ | 91/100 [38:28<01:45, 11.69s/it]
```

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[I 2025-09-16 20:03:28,161] Trial 90 finished with value: 0.35993451981870317 and parameters: {'n_estimators': 200, 'learning_rate': 0.09049615742574411, 'num_leaves': 1740, 'max_depth': 9, 'min_child_samples': 88, 'subsample': 0.6350891941750214, 'colsample_bytree': 0.8276427680710078, 'reg_alpha': 2.8177257322921792e-06, 'reg_lambda': 1.7122947335829997e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  92%|█████████▏| 92/100 [38:39<01:32, 11.61s/it]
[I 2025-09-16 20:03:39,568] Trial 91 finished with value: 0.43907358477603065 and parameters: {'n_estimators': 200, 'learning_rate': 0.011825988530796805, 'num_leaves': 1960, 'max_depth': 9, 'min_child_samples': 75, 'subsample': 0.6780167200426578, 'colsample_bytree': 0.8729937849531596, 'reg_alpha': 2.326959308407462e-07, 'reg_lambda': 0.00016093091644270907}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  93%|█████████▎| 93/100 [38:52<01:23, 11.97s/it]
[I 2025-09-16 20:03:52,393] Trial 92 finished with value: 0.432639440698961 and parameters: {'n_estimators': 300, 'learning_rate': 0.011771494289230862, 'num_leaves': 2120, 'max_depth': 8, 'min_child_samples': 75, 'subsample': 0.6075253407186267, 'colsample_bytree': 0.8737192583439946, 'reg_alpha': 1.1625165986917307e-07, 'reg_lambda': 4.661059484291591e-05}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  94%|█████████▍| 94/100 [39:01<01:06, 11.09s/it]
[I 2025-09-16 20:04:01,435] Trial 93 finished with value: 0.4257555685039144 and parameters: {'n_estimators': 200, 'learning_rate': 0.026981090847110242, 'num_leaves': 1680, 'max_depth': 9, 'min_child_samples': 108, 'subsample': 0.6961497457869827, 'colsample_bytree': 0.8633833149416603, 'reg_alpha': 7.268460322106225e-07, 'reg_lambda': 0.0003013618720879176}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  95%|█████████▌| 95/100 [39:52<01:54, 22.91s/it]
[I 2025-09-16 20:04:51,925] Trial 94 finished with value: 0.3643039556070681 and parameters: {'n_estimators': 1300, 'learning_rate': 0.033074062527879027, 'num_leaves': 2260, 'max_depth': 10, 'min_child_samples': 97, 'subsample': 0.6778057374927114, 'colsample_bytree': 0.8733859618537407, 'reg_alpha': 2.871839494890932e-07, 'reg_lambda': 0.0001884377526242393}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  96%|█████████▌| 96/100 [40:10<01:26, 21.56s/it]
[I 2025-09-16 20:05:10,339] Trial 95 finished with value: 0.3923366499473321 and parameters: {'n_estimators': 400, 'learning_rate': 0.02503344802833772, 'num_leaves': 1860, 'max_depth': 9, 'min_child_samples': 68, 'subsample': 0.7158218032168366, 'colsample_bytree': 0.903066960648308, 'reg_alpha': 6.081724440532384e-06, 'reg_lambda': 0.0001040384968021309}. Best is trial 45 with value: 0.4456428160508864.
Best trial: 45. Best value: 0.445643:  97%|█████████▋| 97/100 [40:29<01:02, 20.77s/it]
```

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[I 2025-09-16 20:05:29,269] Trial 96 finished with value: 0.43911299
295512574 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
1132131536582463 8, 'num_leaves': 1960, 'max_depth': 10, 'min_child_s
amples': 80, 'subsample': 0.6829705297709161, 'colsample_bytree': 0.
8787679511667964, 'reg_alpha': 1.740469302624294e-07, 'reg_lambda':
9.182103056842881e-06}. Best is trial 45 with value: 0.4456428160508
864.
Best trial: 45. Best value: 0.445643:  98%|██████████| 98/100 [40:41
<00:36, 18.26s/it]
[I 2025-09-16 20:05:41,650] Trial 97 finished with value: 0.44013769
14561264 and parameters: {'n_estimators': 200, 'learning_rate': 0.01
8673400262906106, 'num_leaves': 2480, 'max_depth': 10, 'min_child_sa
mples': 89, 'subsample': 0.6836583890074452, 'colsample_bytree': 0.8
816296497948167, 'reg_alpha': 1.5849661478125888e-07, 'reg_lambda':
1.1186740132822356e-05}. Best is trial 45 with value: 0.445642816050
8864.
Best trial: 45. Best value: 0.445643:  99%|██████████| 99/100 [40:54
<00:16, 16.45s/it]
[I 2025-09-16 20:05:53,872] Trial 98 finished with value: 0.43992559
508522 and parameters: {'n_estimators': 200, 'learning_rate': 0.0175
35412355342762, 'num_leaves': 1940, 'max_depth': 10, 'min_child_samp
les': 85, 'subsample': 0.6801771002447561, 'colsample_bytree': 0.880
8844981473426, 'reg_alpha': 1.894169941800382e-06, 'reg_lambda': 9.9
02978101472302e-06}. Best is trial 45 with value: 0.445642816050886
4.
Best trial: 45. Best value: 0.445643: 100%|██████████| 100/100 [41:0
5<00:00, 24.65s/it]
[I 2025-09-16 20:06:05,289] Trial 99 finished with value: 0.41227728
192857194 and parameters: {'n_estimators': 200, 'learning_rate': 0.0
3754938793046787, 'num_leaves': 2540, 'max_depth': 10, 'min_child_sa
mples': 78, 'subsample': 0.6797454748010485, 'colsample_bytree': 0.8
802887362297731, 'reg_alpha': 1.7432038331548869e-06, 'reg_lambda':
9.050568251963762e-06}. Best is trial 45 with value: 0.4456428160508
864.

--- Hyperparameter Optimization Complete ---

Best trial:
  Value: 0.4456428160508864
  Params:
    n_estimators: 200
    learning_rate: 0.01032565119154107
    num_leaves: 1440
    max_depth: 10
    min_child_samples: 45
    subsample: 0.9643946012301383
    colsample_bytree: 0.8979866059177901
    reg_alpha: 1.2879201869482782e-08
    reg_lambda: 2.74426603318653e-06
```

In [70]:

```
def objective_xgb(trial):
    """
    This is the objective function that Optuna will optimize.
    A 'trial' is a single run of the model with a specific set of h
    """
```

```
    params = {
        'n_estimators': trial.suggest_int('n_estimators', 100, 2000
        'learning_rate': trial.suggest_float('learning_rate', 0.01,
        'max_depth': trial.suggest_int('max_depth', 3, 12),
        'subsample': trial.suggest_float('subsample', 0.6, 1.0),
        'colsample_bytree': trial.suggest_float('colsample_bytree',
        'gamma': trial.suggest_float('gamma', 1e-8, 1.0, log=True),
        'reg_alpha': trial.suggest_float('reg_alpha', 1e-8, 10.0, l
        'reg_lambda': trial.suggest_float('reg_lambda', 1e-8, 10.0,
        'eval_metric': 'logloss',
        'random_state': 42
    }

    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor_engineered),
        ('smote', SMOTE(random_state=seed)),
        ('classifier', XGBClassifier(**params))
    ])

    cv_strategy = StratifiedKFold(n_splits=5, shuffle=True, random_
    score = cross_val_score(
        pipeline, X_train, y_train, cv=cv_strategy, scoring='f1', n
    ).mean()
    return score

study_xgb = optuna.create_study(direction='maximize', study_name='X
print("\n--- Starting Hyperparameter Optimization for XGBoost Class
study_xgb.optimize(objective_xgb, n_trials=100, show_progress_bar=T
print("\n--- Hyperparameter Optimization Complete ---\n")
print("Best trial:")
trial = study_xgb.best_trial
print(f"  Value: {trial.value}")
print("  Params: ")
for key, value in trial.params.items():
    print(f"    {key}: {value}")
```

```
[I 2025-09-16 20:06:05,311] A new study created in memory with name:
XGBoost Classifier Optimization
--- Starting Hyperparameter Optimization for XGBoost Classifier ---

Best trial: 0. Best value: 0.359218:   1%|          | 1/100 [00:08<1
4:40,  8.90s/it]
[I 2025-09-16 20:06:14,210] Trial 0 finished with value: 0.359218145
9595275 and parameters: {'n_estimators': 700, 'learning_rate': 0.255
12077788342663, 'max_depth': 5, 'subsample': 0.7263929896077592, 'co
lsample_bytree': 0.7952750084599102, 'gamma': 0.5083279407935706, 'r
eg_alpha': 1.180284123979695, 'reg_lambda': 1.6739756879825525e-07}.
Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   2%|▏         | 2/100 [00:34<3
0:46, 18.84s/it]
[I 2025-09-16 20:06:40,016] Trial 1 finished with value: 0.353185365
78669585 and parameters: {'n_estimators': 800, 'learning_rate': 0.29
223353122042545, 'max_depth': 10, 'subsample': 0.9400898280778509, '
colsample_bytree': 0.7111445737299767, 'gamma': 5.310799029726833e-0
7, 'reg_alpha': 0.00041468736933715625, 'reg_lambda': 2.384243516441
0842}. Best is trial 0 with value: 0.3592181459595275.
```

```
Best trial: 0. Best value: 0.359218:   3%|▌         | 3/100 [00:46<25:33, 15.81s/it]
[I 2025-09-16 20:06:52,213] Trial 2 finished with value: 0.3511229860448294 and parameters: {'n_estimators': 700, 'learning_rate': 0.26672705946979813, 'max_depth': 7, 'subsample': 0.9744315539249055, 'colsample_bytree': 0.6736147126208472, 'gamma': 1.617423722636496e-05, 'reg_alpha': 0.03017081078605475, 'reg_lambda': 0.0011880465213766596}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   4%|▌         | 4/100 [00:55<21:02, 13.15s/it]
[I 2025-09-16 20:07:01,292] Trial 3 finished with value: 0.34669745911409855 and parameters: {'n_estimators': 1200, 'learning_rate': 0.11308169531417886, 'max_depth': 9, 'subsample': 0.9616817933531003, 'colsample_bytree': 0.9381106877616625, 'gamma': 0.6911900105453664, 'reg_alpha': 8.342761332064744e-08, 'reg_lambda': 0.03522129728727152}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   5%|▌         | 5/100 [02:15<58:33, 36.98s/it]
[I 2025-09-16 20:08:20,532] Trial 4 finished with value: 0.3503441683693248 and parameters: {'n_estimators': 1900, 'learning_rate': 0.03859847632647793, 'max_depth': 11, 'subsample': 0.9544556995927647, 'colsample_bytree': 0.6902253498109918, 'gamma': 4.554621082337828e-06, 'reg_alpha': 3.1472444803808994e-06, 'reg_lambda': 4.029587955252749e-05}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   6%|▌         | 6/100 [03:05<1:05:11, 41.61s/it]
[I 2025-09-16 20:09:11,120] Trial 5 finished with value: 0.339692759529918 and parameters: {'n_estimators': 1400, 'learning_rate': 0.18354147395779388, 'max_depth': 11, 'subsample': 0.7334742446023554, 'colsample_bytree': 0.939952961026596, 'gamma': 5.832057533708263e-07, 'reg_alpha': 0.0011811352642399026, 'reg_lambda': 3.188569301883786e-07}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   7%|▋         | 7/100 [03:11<46:20, 29.89s/it]
[I 2025-09-16 20:09:16,891] Trial 6 finished with value: 0.3537321027455853 and parameters: {'n_estimators': 300, 'learning_rate': 0.167451343609208, 'max_depth': 7, 'subsample': 0.9040963280122305, 'colsample_bytree': 0.7142372773346671, 'gamma': 1.9694292463412994e-08, 'reg_alpha': 0.00038282783569524263, 'reg_lambda': 2.2608834468424487e-08}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   8%|▊         | 8/100 [03:44<47:33, 31.01s/it]
[I 2025-09-16 20:09:50,298] Trial 7 finished with value: 0.3445216497957385 and parameters: {'n_estimators': 900, 'learning_rate': 0.294777915810815, 'max_depth': 11, 'subsample': 0.685757236984652 5, 'colsample_bytree': 0.9070467013370517, 'gamma': 6.123674177657689e-08, 'reg_alpha': 2.1682423442471012e-06, 'reg_lambda': 2.898956350447298e-08}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:   9%|▉         | 9/100 [04:14<46:28, 30.64s/it]
```

```
[I 2025-09-16 20:10:20,116] Trial 8 finished with value: 0.342765504
91152624 and parameters: {'n_estimators': 1500, 'learning_rate': 0.1
8538587245158572, 'max_depth': 7, 'subsample': 0.8595352590392265, '
colsample_bytree': 0.9430530418264707, 'gamma': 1.7682792182704292e-
07, 'reg_alpha': 3.249856547385235e-05, 'reg_lambda': 3.134093036640
667e-05}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:  10%|█         | 10/100 [04:44<
45:24, 30.27s/it]
[I 2025-09-16 20:10:49,561] Trial 9 finished with value: 0.348789113
2641965 and parameters: {'n_estimators': 1400, 'learning_rate': 0.16
876683725442307, 'max_depth': 7, 'subsample': 0.6744340601684836, 'c
olsample_bytree': 0.9815937082033824, 'gamma': 0.0001508254164827587
6, 'reg_alpha': 1.9959749002165158e-07, 'reg_lambda': 8.180543586600
625e-08}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:  11%|█         | 11/100 [04:46<
32:00, 21.58s/it]
[I 2025-09-16 20:10:51,434] Trial 10 finished with value: 0.33016534
506709755 and parameters: {'n_estimators': 200, 'learning_rate': 0.2
333410308647308, 'max_depth': 3, 'subsample': 0.6102929577965459, 'c
olsample_bytree': 0.819682168058811, 'gamma': 0.6051217408553423, 'r
eg_alpha': 3.562498694541104, 'reg_lambda': 1.1351643092489866e-06}.
Best is trial 0 with value: 0.3592181459595275.
Best trial: 0. Best value: 0.359218:  12%|█         | 12/100 [04:48<
23:15, 15.86s/it]
[I 2025-09-16 20:10:54,211] Trial 11 finished with value: 0.32835359
542869746 and parameters: {'n_estimators': 300, 'learning_rate': 0.1
1623646074355005, 'max_depth': 4, 'subsample': 0.837143067542968, 'c
olsample_bytree': 0.782513914367181, 'gamma': 0.004930371805096329,
'reg_alpha': 6.3487399540295995, 'reg_lambda': 2.670113575750276e-0
6}. Best is trial 0 with value: 0.3592181459595275.
Best trial: 12. Best value: 0.363746:  13%|█         | 13/100 [04:53
<18:14, 12.58s/it]
[I 2025-09-16 20:10:59,257] Trial 12 finished with value: 0.36374562
55349059 and parameters: {'n_estimators': 500, 'learning_rate': 0.22
86933661141488, 'max_depth': 5, 'subsample': 0.7761507176489127, 'co
lsample_bytree': 0.6054043022021642, 'gamma': 0.006829823118648862,
'reg_alpha': 0.08180739226186069, 'reg_lambda': 1.7650983074918607e-
08}. Best is trial 12 with value: 0.3637456255349059.
Best trial: 12. Best value: 0.363746:  14%|█▍        | 14/100 [04:59
<15:11, 10.59s/it]
[I 2025-09-16 20:11:05,251] Trial 13 finished with value: 0.35586603
244459586 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
236764517498532, 'max_depth': 5, 'subsample': 0.7715028288127009, 'c
olsample_bytree': 0.6398301229989518, 'gamma': 0.015225419985105394,
'reg_alpha': 0.12987550655467733, 'reg_lambda': 4.647690574807136e-0
6}. Best is trial 12 with value: 0.3637456255349059.
Best trial: 12. Best value: 0.363746:  15%|█▌        | 15/100 [05:04
<12:34,  8.88s/it]
[I 2025-09-16 20:11:10,164] Trial 14 finished with value: 0.36323765
948594616 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
2582413391587394, 'max_depth': 5, 'subsample': 0.7952398635060216, '
colsample_bytree': 0.6011593702866604, 'gamma': 0.011366581131788903
3, 'reg_alpha': 0.07706415367313905, 'reg_lambda': 0.001844128966137
3043}. Best is trial 12 with value: 0.3637456255349059.
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Best trial: 15. Best value: 0.365308:  16%|██        | 16/100 [05:09
<10:47,  7.71s/it]
[I 2025-09-16 20:11:15,147] Trial 15 finished with value: 0.36530796
847352265 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
106173205641995, 'max_depth': 5, 'subsample': 0.8033349278290809, 'c
olsample_bytree': 0.6207534906207018, 'gamma': 0.002091341564932064
7, 'reg_alpha': 0.01871498134800673, 'reg_lambda': 0.007345148233751
425}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  17%|██        | 17/100 [05:11
<08:01,  5.80s/it]
[I 2025-09-16 20:11:16,512] Trial 16 finished with value: 0.28890033
17833048 and parameters: {'n_estimators': 100, 'learning_rate': 0.11
619759378597071, 'max_depth': 3, 'subsample': 0.8475032335937436, 'c
olsample_bytree': 0.6007978613021537, 'gamma': 0.000219687128262046 5
6, 'reg_alpha': 0.003537608880533854, 'reg_lambda': 0.02894448776412
105}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  18%|██        | 18/100 [05:25
<11:18,  8.27s/it]
[I 2025-09-16 20:11:30,540] Trial 17 finished with value: 0.35753761
24920469 and parameters: {'n_estimators': 1000, 'learning_rate': 0.2
1033946489300875, 'max_depth': 6, 'subsample': 0.7695258471249943, '
colsample_bytree': 0.7541918557832284, 'gamma': 0.00116478296153921
9, 'reg_alpha': 0.008069996736406357, 'reg_lambda': 2.12598706072441
16}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  19%|██        | 19/100 [05:37
<12:41,  9.40s/it]
[I 2025-09-16 20:11:42,579] Trial 18 finished with value: 0.35066173
422167846 and parameters: {'n_estimators': 400, 'learning_rate': 0.1
397877461985445, 'max_depth': 9, 'subsample': 0.9021127851675041, '
colsample_bytree': 0.8570531271969992, 'gamma': 0.05873207724529701,
'reg_alpha': 0.37814738575807694, 'reg_lambda': 0.02619767668822029
3}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  20%|██        | 20/100 [05:44
<11:47,  8.84s/it]
[I 2025-09-16 20:11:50,104] Trial 19 finished with value: 0.34511009
598588527 and parameters: {'n_estimators': 1100, 'learning_rate': 0.
06713716700332252, 'max_depth': 4, 'subsample': 0.8066562189581901,
'colsample_bytree': 0.6328229563248674, 'gamma': 0.00069966382764839
14, 'reg_alpha': 0.014700822475532954, 'reg_lambda': 9.7329239425319
38e-05}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  21%|██        | 21/100 [05:51
<10:45,  8.18s/it]
[I 2025-09-16 20:11:56,732] Trial 20 finished with value: 0.35270106
07456104 and parameters: {'n_estimators': 500, 'learning_rate': 0.25
44360888642697, 'max_depth': 6, 'subsample': 0.7212512207135682, 'co
lsample_bytree': 0.6544863562804109, 'gamma': 2.4788700830052747e-0
5, 'reg_alpha': 6.666451368220396e-05, 'reg_lambda': 0.3114057742742
407}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  22%|██        | 22/100 [05:56
<09:19,  7.17s/it]
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[I 2025-09-16 20:12:01,571] Trial 21 finished with value: 0.36285416
232941575 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
1060507393665434, 'max_depth': 5, 'subsample': 0.7960248439779447, '
colsample_bytree': 0.6077941531486176, 'gamma': 0.04633714579076591,
'reg_alpha': 0.0813573580137204, 'reg_lambda': 0.001633912398125463
5}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  23%|██        | 23/100 [05:57
<07:04,  5.51s/it]
[I 2025-09-16 20:12:03,190] Trial 22 finished with value: 0.29034909
433159145 and parameters: {'n_estimators': 100, 'learning_rate': 0.1
951319570667307, 'max_depth': 4, 'subsample': 0.8128734609558673, 'c
olsample_bytree': 0.605474013382251, 'gamma': 0.004970159450406148,
'reg_alpha': 0.408615221888936, 'reg_lambda': 0.002511687788173052}.
Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  24%|██        | 24/100 [06:04
<07:34,  5.98s/it]
[I 2025-09-16 20:12:10,273] Trial 23 finished with value: 0.35777801
874131937 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
3747033104875487, 'max_depth': 6, 'subsample': 0.7641338809445619, '
colsample_bytree': 0.7384809042996427, 'gamma': 0.002776295860263655
3, 'reg_alpha': 0.050933911453314724, 'reg_lambda': 0.00027270180611
21589}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  25%|██        | 25/100 [06:19
<10:51,  8.69s/it]
[I 2025-09-16 20:12:25,283] Trial 24 finished with value: 0.35150677
68686141 and parameters: {'n_estimators': 800, 'learning_rate': 0.26
97373468430798, 'max_depth': 8, 'subsample': 0.8745273864730871, 'co
lsample_bytree': 0.6602756425505235, 'gamma': 0.08351026885201161, '
reg_alpha': 0.008022310140736504, 'reg_lambda': 0.00466295057742548
7}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  26%|██        | 26/100 [06:23
<08:45,  7.10s/it]
[I 2025-09-16 20:12:28,670] Trial 25 finished with value: 0.34598627
084715616 and parameters: {'n_estimators': 300, 'learning_rate': 0.1
5338590281851872, 'max_depth': 5, 'subsample': 0.6818573044995893, '
colsample_bytree': 0.6324786734657695, 'gamma': 0.01850038005089830
7, 'reg_alpha': 0.002123482795971532, 'reg_lambda': 0.21721613119406
03}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  27%|██        | 27/100 [06:28
<07:45,  6.38s/it]
[I 2025-09-16 20:12:33,369] Trial 26 finished with value: 0.35650872
094968544 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
0756420563831612, 'max_depth': 4, 'subsample': 0.820902509328658, 'c
olsample_bytree': 0.6926829560868754, 'gamma': 0.000618873897960545
9, 'reg_alpha': 0.46717708399620933, 'reg_lambda': 0.000316133666836
9984}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  28%|██        | 28/100 [06:40
<09:46,  8.15s/it]
[I 2025-09-16 20:12:45,638] Trial 27 finished with value: 0.35807292
42492468 and parameters: {'n_estimators': 900, 'learning_rate': 0.23
753354141311714, 'max_depth': 6, 'subsample': 0.7792954376225523, 'c
olsample_bytree': 0.6273141392320807, 'gamma': 0.14227914540694034,
'reg_alpha': 2.07045167573927, 'reg_lambda': 0.010800388713696115}.
Best is trial 15 with value: 0.36530796847352265.
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Best trial: 15. Best value: 0.365308:  29%|███       | 29/100 [06:50
<10:13,  8.64s/it]
[I 2025-09-16 20:12:55,439] Trial 28 finished with value: 0.36212087
329602244 and parameters: {'n_estimators': 1900, 'learning_rate': 0.
2756311208472221, 'max_depth': 3, 'subsample': 0.7381780120735587, '
colsample_bytree': 0.6733255518217443, 'gamma': 0.01697877983345011
7, 'reg_alpha': 1.3213215187694494e-08, 'reg_lambda': 8.139847095953
994e-06}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  30%|███       | 30/100 [06:57
<09:39,  8.27s/it]
[I 2025-09-16 20:13:02,855] Trial 29 finished with value: 0.35638140
950504027 and parameters: {'n_estimators': 700, 'learning_rate': 0.2
420261124288904, 'max_depth': 5, 'subsample': 0.8827266524512564, '
colsample_bytree': 0.733592901622015, 'gamma': 5.834167679842500 5e-0
5, 'reg_alpha': 0.9660467726075829, 'reg_lambda': 0.1838959530631782
7}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 15. Best value: 0.365308:  31%|███       | 31/100 [07:07
<09:57,  8.66s/it]
[I 2025-09-16 20:13:12,400] Trial 30 finished with value: 0.35337391
195618617 and parameters: {'n_estimators': 400, 'learning_rate': 0.1
391191744654804, 'max_depth': 8, 'subsample': 0.7080706296521062, 'c
olsample_bytree': 0.8242659223989188, 'gamma': 0.18275365975653152,
'reg_alpha': 0.13947031601730037, 'reg_lambda': 0.000575117368655010
4}. Best is trial 15 with value: 0.36530796847352265.
Best trial: 31. Best value: 0.366989:  32%|███       | 32/100 [07:12
<08:35,  7.58s/it]
[I 2025-09-16 20:13:17,457] Trial 31 finished with value: 0.36698910
8702719 and parameters: {'n_estimators': 500, 'learning_rate': 0.216
0646626097383, 'max_depth': 5, 'subsample': 0.7837338636029024, 'col
sample_bytree': 0.6001513908234241, 'gamma': 0.028269185384032322, '
reg_alpha': 0.07114431395272847, 'reg_lambda': 0.00424665402421010
1}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  33%|███       | 33/100 [07:17
<07:37,  6.83s/it]
[I 2025-09-16 20:13:22,549] Trial 32 finished with value: 0.35907858
015125216 and parameters: {'n_estimators': 700, 'learning_rate': 0.2
1545486926352608, 'max_depth': 4, 'subsample': 0.7441341611495927, '
colsample_bytree': 0.602254286106712, 'gamma': 0.002390517516215395,
'reg_alpha': 0.019534775083518245, 'reg_lambda': 0.0156532261127808
6}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  34%|███▍      | 34/100 [07:25
<07:50,  7.13s/it]
[I 2025-09-16 20:13:30,383] Trial 33 finished with value: 0.35277177
073358734 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
5621405501577466, 'max_depth': 6, 'subsample': 0.8336994469626716, '
colsample_bytree': 0.6507913654505331, 'gamma': 0.0109472559229701,
'reg_alpha': 0.04373595744250339, 'reg_lambda': 0.003750432357050299
6}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  35%|███▌      | 35/100 [07:29
<06:43,  6.21s/it]
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[I 2025-09-16 20:13:34,428] Trial 34 finished with value: 0.36217464
892561163 and parameters: {'n_estimators': 400, 'learning_rate': 0.1
953391821703755, 'max_depth': 5, 'subsample': 0.7924701829765276, 'c
olsample_bytree': 0.6183195540045969, 'gamma': 0.00029235950334479457
7, 'reg_alpha': 0.0009408989554949586, 'reg_lambda': 0.1014320856685
9473}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  36%|███▋      | 36/100 [07:35
<06:47,  6.37s/it]
[I 2025-09-16 20:13:41,196] Trial 35 finished with value: 0.35745596
31535005 and parameters: {'n_estimators': 800, 'learning_rate': 0.27
928869789448824, 'max_depth': 5, 'subsample': 0.9942479732583299, 'c
olsample_bytree': 0.6846485315713309, 'gamma': 0.001227594848169668,
'reg_alpha': 9.600276522797879, 'reg_lambda': 8.078266012116877}. Be
st is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  37%|███▋      | 37/100 [07:37
<05:20,  5.08s/it]
[I 2025-09-16 20:13:43,256] Trial 36 finished with value: 0.33735379
03313532 and parameters: {'n_estimators': 200, 'learning_rate': 0.25
25907252000587, 'max_depth': 4, 'subsample': 0.7467881425876324, 'co
lsample_bytree': 0.6600641933531612, 'gamma': 0.2720219220780974, 'r
eg_alpha': 9.406718748028658e-05, 'reg_lambda': 0.000141406315822941
62}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  38%|███▊      | 38/100 [08:01
<10:57, 10.61s/it]
[I 2025-09-16 20:14:06,771] Trial 37 finished with value: 0.34852108
217602007 and parameters: {'n_estimators': 1200, 'learning_rate': 0.
18389580080310386, 'max_depth': 12, 'subsample': 0.9253968793203995,
'colsample_bytree': 0.6980633680280528, 'gamma': 0.0433630397425265
2, 'reg_alpha': 0.25471923931581225, 'reg_lambda': 2.5955540102526e-
05}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  39%|███▉      | 39/100 [08:09
<09:57,  9.80s/it]
[I 2025-09-16 20:14:14,679] Trial 38 finished with value: 0.35988249
464105415 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
270365001181743, 'max_depth': 6, 'subsample': 0.7076679613649937, 'c
olsample_bytree': 0.6270888703596946, 'gamma': 0.0065610911272509335
5, 'reg_alpha': 0.04111621766194238, 'reg_lambda': 0.001058884257005
5336}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  40%|████      | 40/100 [08:25
<11:36, 11.61s/it]
[I 2025-09-16 20:14:30,522] Trial 39 finished with value: 0.35091657
089930967 and parameters: {'n_estimators': 900, 'learning_rate': 0.1
670692972323890 9, 'max_depth': 7, 'subsample': 0.8218368461324032, '
colsample_bytree': 0.7202610279285916, 'gamma': 2.3518665118587784e-
06, 'reg_alpha': 0.005049896113790488, 'reg_lambda': 1.0336841402850
463}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  41%|████      | 41/100 [08:30
<09:28,  9.64s/it]
[I 2025-09-16 20:14:35,569] Trial 40 finished with value: 0.35592838
67296662 and parameters: {'n_estimators': 200, 'learning_rate': 0.28
41177931091914, 'max_depth': 8, 'subsample': 0.6460729841085722, 'co
lsample_bytree': 0.6723060340088965, 'gamma': 0.03374406488655542, '
reg_alpha': 1.292737598636094, 'reg_lambda': 0.004851176669155749}.
Best is trial 31 with value: 0.366989108702719.
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Best trial: 31. Best value: 0.366989:  42%|████      | 42/100 [08:34<07:48,  8.07s/it]
[I 2025-09-16 20:14:39,979] Trial 41 finished with value: 0.361612355580797 and parameters: {'n_estimators': 500, 'learning_rate': 0.2059630922992036, 'max_depth': 5, 'subsample': 0.7943693623743445, 'colsample_bytree': 0.6122641297335751, 'gamma': 0.9474229863678078, 'reg_alpha': 0.08789024206086037, 'reg_lambda': 0.002395914065745672}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  43%|████      | 43/100 [08:39<06:48,  7.17s/it]
[I 2025-09-16 20:14:45,028] Trial 42 finished with value: 0.3588388524531938 and parameters: {'n_estimators': 500, 'learning_rate': 0.2178887317136105, 'max_depth': 5, 'subsample': 0.7581178117310371, 'colsample_bytree': 0.6440079471637061, 'gamma': 0.02830870303604282, 'reg_alpha': 0.01647331431784768, 'reg_lambda': 0.0010276493313098572}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  44%|████      | 44/100 [08:42<05:25,  5.82s/it]
[I 2025-09-16 20:14:47,692] Trial 43 finished with value: 0.338286958752178 and parameters: {'n_estimators': 400, 'learning_rate': 0.19065045431882602, 'max_depth': 3, 'subsample': 0.7903835209113762, 'colsample_bytree': 0.6006260250081316, 'gamma': 0.10773057286013864, 'reg_alpha': 0.10784006073896578, 'reg_lambda': 0.0774490823231079}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  45%|████▌     | 45/100 [08:50<05:57,  6.50s/it]
[I 2025-09-16 20:14:55,793] Trial 44 finished with value: 0.35975397384663294 and parameters: {'n_estimators': 700, 'learning_rate': 0.24654168173416607, 'max_depth': 6, 'subsample': 0.856353842980151, 'colsample_bytree': 0.621191021868915, 'gamma': 0.3263248207953624, 'reg_alpha': 0.0008970455143112484, 'reg_lambda': 0.009119605885109424}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  46%|████▌     | 46/100 [08:53<04:49,  5.36s/it]
[I 2025-09-16 20:14:58,507] Trial 45 finished with value: 0.36014170692750286 and parameters: {'n_estimators': 300, 'learning_rate': 0.2640150267131577, 'max_depth': 4, 'subsample': 0.7879200875015355, 'colsample_bytree': 0.6411202909794464, 'gamma': 0.00233611037766157, 'reg_alpha': 1.217664171880239, 'reg_lambda': 0.00012232762311318638}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  47%|████▋     | 47/100 [09:19<10:23, 11.76s/it]
[I 2025-09-16 20:15:25,176] Trial 46 finished with value: 0.3420511448284253 and parameters: {'n_estimators': 1700, 'learning_rate': 0.298607935514108, 'max_depth': 7, 'subsample': 0.8385244466198921, 'colsample_bytree': 0.6181723334538801, 'gamma': 0.006996583163677835, 'reg_alpha': 0.17793816791876532, 'reg_lambda': 0.0007273858302229218}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  48%|████▊     | 48/100 [09:25<08:41, 10.03s/it]
```

```
[I 2025-09-16 20:15:31,186] Trial 47 finished with value: 0.36235421
903065884 and parameters: {'n_estimators': 600, 'learning_rate': 0.1
7791211292366185, 'max_depth': 5, 'subsample': 0.8070933722307045, '
colsample_bytree': 0.6685258853535864, 'gamma': 0.0573841341403862,
'reg_alpha': 5.920034150933067e-06, 'reg_lambda': 3.434480861154682e
-07}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  49%|█████     | 49/100 [09:32
<07:41,  9.05s/it]
```

```
[I 2025-09-16 20:15:37,949] Trial 48 finished with value: 0.35918339
507653757 and parameters: {'n_estimators': 800, 'learning_rate': 0.2
0350492446866253, 'max_depth': 4, 'subsample': 0.7566090425817535, '
colsample_bytree': 0.9053805277643513, 'gamma': 7.573556167729912e-0
5, 'reg_alpha': 0.04219336574389392, 'reg_lambda': 0.048744419274451
764}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  50%|█████     | 50/100 [09:38
<06:37,  7.95s/it]
```

```
[I 2025-09-16 20:15:43,325] Trial 49 finished with value: 0.36319891
87965397 and parameters: {'n_estimators': 300, 'learning_rate': 0.22
901668817546392, 'max_depth': 7, 'subsample': 0.7254146981971034, 'c
olsample_bytree': 0.6444633239773542, 'gamma': 0.011958994349217647,
'reg_alpha': 0.0025914010544263837, 'reg_lambda': 1.6671197907586183
e-05}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  51%|█████     | 51/100 [09:44
<06:13,  7.62s/it]
```

```
[I 2025-09-16 20:15:50,177] Trial 50 finished with value: 0.35446416
169062445 and parameters: {'n_estimators': 200, 'learning_rate': 0.2
27671237668324, 'max_depth': 9, 'subsample': 0.6635276342124781, 'c
olsample_bytree': 0.7644766798801115, 'gamma': 0.000396140636866925
4, 'reg_alpha': 0.00023540858284407733, 'reg_lambda': 4.026676395177
6095e-08}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  52%|█████     | 52/100 [09:50
<05:38,  7.05s/it]
```

```
[I 2025-09-16 20:15:55,882] Trial 51 finished with value: 0.35208765
763660343 and parameters: {'n_estimators': 400, 'learning_rate': 0.2
1685140232855782, 'max_depth': 6, 'subsample': 0.7078899417522052, '
colsample_bytree': 0.6471264936439945, 'gamma': 0.010217228501038933
3, 'reg_alpha': 0.0025822978061782165, 'reg_lambda': 1.2865956288461
787e-08}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  53%|█████     | 53/100 [09:54
<04:53,  6.24s/it]
```

```
[I 2025-09-16 20:16:00,233] Trial 52 finished with value: 0.31059338
312410756 and parameters: {'n_estimators': 300, 'learning_rate': 0.0
11733449351839759, 'max_depth': 5, 'subsample': 0.7741193917502698,
'colsample_bytree': 0.6003842527871908, 'gamma': 0.00314177271725481
47, 'reg_alpha': 0.010779380101776832, 'reg_lambda': 8.1534406552549
95e-07}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  54%|█████▍    | 54/100 [10:12
<07:20,  9.58s/it]
```

```
[I 2025-09-16 20:16:17,608] Trial 53 finished with value: 0.35369063
774937437 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
3213750414368203, 'max_depth': 10, 'subsample': 0.7209284821863469,
'colsample_bytree': 0.618761708015716, 'gamma': 0.00137869883735307
86, 'reg_alpha': 0.02483398566419555 2, 'reg_lambda': 1.11588694146608
05e-05}. Best is trial 31 with value: 0.366989108702719.
```

```
Best trial: 31. Best value: 0.366989:  55%|█████▌    | 55/100 [10:17
<06:06,  8.15s/it]
[I 2025-09-16 20:16:22,428] Trial 54 finished with value: 0.34901266
82460337 and parameters: {'n_estimators': 300, 'learning_rate': 0.16
9183261793377, 'max_depth': 6, 'subsample': 0.7304116935787185, 'col
sample_bytree': 0.6388798178360894, 'gamma': 0.023998283655021192, '
reg_alpha': 0.006257031598487748, 'reg_lambda': 0.001878512498242462
4}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  56%|█████▌    | 56/100 [10:23
<05:41,  7.76s/it]
[I 2025-09-16 20:16:29,287] Trial 55 finished with value: 0.36640513
93967932 and parameters: {'n_estimators': 600, 'learning_rate': 0.19
906106189977066, 'max_depth': 5, 'subsample': 0.8225013425948475, 'c
olsample_bytree': 0.615267714914541, 'gamma': 0.011245577900381058,
'reg_alpha': 0.07638941715099228, 'reg_lambda': 4.818445889705685e-0
5}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  57%|█████▋    | 57/100 [10:26
<04:29,  6.27s/it]
[I 2025-09-16 20:16:32,079] Trial 56 finished with value: 0.33451035
885132774 and parameters: {'n_estimators': 100, 'learning_rate': 0.1
9854060740754872, 'max_depth': 7, 'subsample': 0.8222113393514129, '
colsample_bytree': 0.9982686088330792, 'gamma': 0.00524471487270106
6, 'reg_alpha': 0.5280672553328231, 'reg_lambda': 6.698918397789647e
-05}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  58%|█████▊    | 58/100 [10:38
<05:27,  7.81s/it]
[I 2025-09-16 20:16:43,464] Trial 57 finished with value: 0.34569058
590054025 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
2064361551673004, 'max_depth': 7, 'subsample': 0.874959335885107, 'c
olsample_bytree': 0.6329509723928142, 'gamma': 0.013299859385137511,
'reg_alpha': 0.0018632379374532613, 'reg_lambda': 1.4283855823626377
e-05}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  59%|█████▉    | 59/100 [10:44
<04:58,  7.28s/it]
[I 2025-09-16 20:16:49,512] Trial 58 finished with value: 0.33921128
600323824 and parameters: {'n_estimators': 1000, 'learning_rate': 0.
08955176812435997, 'max_depth': 3, 'subsample': 0.8524802285352113,
'colsample_bytree': 0.6821933954475085, 'gamma': 0.00091611767769082
09, 'reg_alpha': 0.0003080978567614832, 'reg_lambda': 1.939601931612
5666e-07}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  60%|██████    | 60/100 [10:47
<04:08,  6.22s/it]
[I 2025-09-16 20:16:53,262] Trial 59 finished with value: 0.34248063
354924213 and parameters: {'n_estimators': 400, 'learning_rate': 0.1
5365122140769097, 'max_depth': 4, 'subsample': 0.75462018347199, 'co
lsample_bytree': 0.6574138032520955, 'gamma': 1.2117190121066675e-0
8, 'reg_alpha': 0.22013554556409484, 'reg_lambda': 2.061270393048642
3e-06}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  61%|██████    | 61/100 [10:55
<04:20,  6.69s/it]
```

```
[I 2025-09-16 20:17:01,037] Trial 60 finished with value: 0.36684357
329663053 and parameters: {'n_estimators': 700, 'learning_rate': 0.2
447886300149981, 'max_depth': 5, 'subsample': 0.7735629158486674, 'c
olsample_bytree': 0.7066650705639143, 'gamma': 0.003981454145849866,
'reg_alpha': 0.07089627405415189, 'reg_lambda': 0.000358687098568529
4}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  62%|██████    | 62/100 [11:03
<04:21,  6.88s/it]
[I 2025-09-16 20:17:08,384] Trial 61 finished with value: 0.35785825
28960872 and parameters: {'n_estimators': 700, 'learning_rate': 0.24
65398295035828, 'max_depth': 5, 'subsample': 0.7768765105006803, 'co
lsample_bytree': 0.614730199334071, 'gamma': 0.002447214226609167, '
reg_alpha': 0.07392421922186335, 'reg_lambda': 0.000309461260674255
7}. Best is trial 31 with value: 0.366989108702719.
Best trial: 31. Best value: 0.366989:  63%|██████    | 63/100 [11:15
<05:19,  8.63s/it]
[I 2025-09-16 20:17:21,102] Trial 62 finished with value: 0.35052729
648548997 and parameters: {'n_estimators': 800, 'learning_rate': 0.2
6611840396743003, 'max_depth': 6, 'subsample': 0.8054187098735157, '
colsample_bytree': 0.712489994016947, 'gamma': 0.008676668365653221,
'reg_alpha': 0.021102380890362343, 'reg_lambda': 4.160009048851773e-
05}. Best is trial 31 with value: 0.366989108702719.
Best trial: 63. Best value: 0.368089:  64%|██████    | 64/100 [11:22
<04:46,  7.97s/it]
[I 2025-09-16 20:17:27,516] Trial 63 finished with value: 0.36808887
92756013 and parameters: {'n_estimators': 500, 'learning_rate': 0.23
070537010502126, 'max_depth': 5, 'subsample': 0.7799609753789188, 'c
olsample_bytree': 0.6376980598132558, 'gamma': 0.004149789577432561,
'reg_alpha': 3.39455861552526, 'reg_lambda': 0.0005094339148476729}.
Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  65%|██████    | 65/100 [11:29
<04:28,  7.67s/it]
[I 2025-09-16 20:17:34,476] Trial 64 finished with value: 0.35814930
749300383 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
3975666839286802, 'max_depth': 5, 'subsample': 0.78239264072242, 'co
lsample_bytree': 0.7011642515037779, 'gamma': 0.00433621785823286, '
reg_alpha': 2.797937879018131, 'reg_lambda': 0.0005353255701889961}.
Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  66%|██████    | 66/100 [11:34
<03:59,  7.05s/it]
[I 2025-09-16 20:17:40,082] Trial 65 finished with value: 0.35549231
2822059 and parameters: {'n_estimators': 600, 'learning_rate': 0.259
29445613161334, 'max_depth': 4, 'subsample': 0.8358416864739605, 'co
lsample_bytree': 0.630198597571936, 'gamma': 0.0014149078357765957,
'reg_alpha': 0.7937660623897159, 'reg_lambda': 0.01710040896389239
7}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  67%|██████    | 67/100 [11:45
<04:30,  8.20s/it]
[I 2025-09-16 20:17:50,981] Trial 66 finished with value: 0.35320407
73779296 and parameters: {'n_estimators': 700, 'learning_rate': 0.21
233040546423348, 'max_depth': 5, 'subsample': 0.8142605303735916, 'c
olsample_bytree': 0.8091833119475792, 'gamma': 0.000138175176516398б
5, 'reg_alpha': 5.725694337125999, 'reg_lambda': 0.00438705967957073
35}. Best is trial 63 with value: 0.3680888792756013.
```

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Best trial: 63. Best value: 0.368089:  68%|███████   | 68/100 [11:55
<04:38,  8.70s/it]
[I 2025-09-16 20:18:00,843] Trial 67 finished with value: 0.35630728
434331793 and parameters: {'n_estimators': 1200, 'learning_rate': 0.
1782769578260559, 'max_depth': 4, 'subsample': 0.7657323469719782, '
colsample_bytree': 0.6120267963875219, 'gamma': 0.000589763226126958
9, 'reg_alpha': 0.28789749182263724, 'reg_lambda': 0.000225302784147
8138}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  69%|███████   | 69/100 [12:02
<04:10,  8.08s/it]
[I 2025-09-16 20:18:07,481] Trial 68 finished with value: 0.36272891
34696033 and parameters: {'n_estimators': 400, 'learning_rate': 0.22
307828735358803, 'max_depth': 6, 'subsample': 0.8046995654620561, 'c
olsample_bytree': 0.6648169358279513, 'gamma': 0.0815781833066823, '
reg_alpha': 0.05751879605904858, 'reg_lambda': 0.00965036394859267}.
Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  70%|███████   | 70/100 [12:14
<04:44,  9.49s/it]
[I 2025-09-16 20:18:20,253] Trial 69 finished with value: 0.36449656
93097236 and parameters: {'n_estimators': 900, 'learning_rate': 0.24
89094904120437, 'max_depth': 5, 'subsample': 0.8219651229148375, 'co
lsample_bytree': 0.8470777170919129, 'gamma': 0.0036908957873392767,
'reg_alpha': 2.086017351951344, 'reg_lambda': 0.000619397011652996
5}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  71%|███████   | 71/100 [12:27
<05:02, 10.45s/it]
[I 2025-09-16 20:18:32,938] Trial 70 finished with value: 0.35916493
97869482 and parameters: {'n_estimators': 900, 'learning_rate': 0.28
797598462368146, 'max_depth': 5, 'subsample': 0.8312176506623664, 'c
olsample_bytree': 0.8503093212789445, 'gamma': 0.020123287305832342,
'reg_alpha': 2.331583176392547, 'reg_lambda': 5.883276278063056e-0
5}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  72%|███████▏  | 72/100 [12:35
<04:28,  9.57s/it]
[I 2025-09-16 20:18:40,471] Trial 71 finished with value: 0.36210114
82252552 and parameters: {'n_estimators': 600, 'learning_rate': 0.24
766008398982586, 'max_depth': 5, 'subsample': 0.798060258106042, 'co
lsample_bytree': 0.8539549276392959, 'gamma': 0.003329324474883502,
'reg_alpha': 0.6097338004183057, 'reg_lambda': 0.001283340757328749
4}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  73%|███████▎  | 73/100 [12:43
<04:11,  9.30s/it]
[I 2025-09-16 20:18:49,123] Trial 72 finished with value: 0.35353811
476227565 and parameters: {'n_estimators': 800, 'learning_rate': 0.2
368145479065858, 'max_depth': 4, 'subsample': 0.7799997826691902, 'c
olsample_bytree': 0.8698272553534294, 'gamma': 0.006020427897622613,
'reg_alpha': 7.150727774853844, 'reg_lambda': 0.000508346008411693
3}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  74%|███████▍  | 74/100 [12:50
<03:43,  8.58s/it]
```

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[I 2025-09-16 20:18:56,027] Trial 73 finished with value: 0.3587393398401716 and parameters: {'n_estimators': 500, 'learning_rate': 0.2033054119247649, 'max_depth': 5, 'subsample': 0.8197744661293158, 'colsample_bytree': 0.7905087912768582, 'gamma': 0.0016429810335647137, 'reg_alpha': 4.393556342839919, 'reg_lambda': 0.00243443842229171}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  75%|███████▌  | 75/100 [13:02<04:01,  9.66s/it]
[I 2025-09-16 20:19:08,220] Trial 74 finished with value: 0.34964992865262506 and parameters: {'n_estimators': 700, 'learning_rate': 0.275014898766638З, 'max_depth': 6, 'subsample': 0.7469456859511898, 'colsample_bytree': 0.8817955170859233, 'gamma': 0.00045831380981864445, 'reg_alpha': 0.1178127297752743, 'reg_lambda': 0.00021305406692973615}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  76%|███████▌  | 76/100 [13:12<03:48,  9.52s/it]
[I 2025-09-16 20:19:17,418] Trial 75 finished with value: 0.36246185819752824 and parameters: {'n_estimators': 1000, 'learning_rate': 0.2555491683812054, 'max_depth': 4, 'subsample': 0.7684100787042923, 'colsample_bytree': 0.8324345333672307, 'gamma': 0.03405334230662507, 'reg_alpha': 0.3407323992086086, 'reg_lambda': 0.007661188740768113}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  77%|███████▋  | 77/100 [13:32<04:51, 12.69s/it]
[I 2025-09-16 20:19:37,511] Trial 76 finished with value: 0.35721497699842886 and parameters: {'n_estimators': 2000, 'learning_rate': 0.2332670829551417, 'max_depth': 5, 'subsample': 0.7972091178995959, 'colsample_bytree': 0.6230960280668495, 'gamma': 0.020073606216974144, 'reg_alpha': 0.03115517010485159, 'reg_lambda': 0.0006947654336824776}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  78%|███████▊  | 78/100 [13:40<04:10, 11.38s/it]
[I 2025-09-16 20:19:45,834] Trial 77 finished with value: 0.36078642475660555 and parameters: {'n_estimators': 700, 'learning_rate': 0.2112801133040689, 'max_depth': 5, 'subsample': 0.8432279429533331, 'colsample_bytree': 0.7704073681196181, 'gamma': 0.00022579690268696 65, 'reg_alpha': 1.6838218968358267, 'reg_lambda': 0.02462169991047861}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  79%|███████▉  | 79/100 [13:48<03:39, 10.43s/it]
[I 2025-09-16 20:19:54,052] Trial 78 finished with value: 0.36329097882084305 and parameters: {'n_estimators': 600, 'learning_rate': 0.18800419166436833, 'max_depth': 6, 'subsample': 0.8116473089299805, 'colsample_bytree': 0.6077104103221462, 'gamma': 0.00409234660702472, 'reg_alpha': 0.013524757804934076, 'reg_lambda': 0.003699602163437101}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  80%|████████  | 80/100 [13:57<03:15,  9.79s/it]
[I 2025-09-16 20:20:02,347] Trial 79 finished with value: 0.36301056105121887 and parameters: {'n_estimators': 600, 'learning_rate': 0.1895207449296994, 'max_depth': 6, 'subsample': 0.8711483724445617, 'colsample_bytree': 0.6116767669300344, 'gamma': 0.0018895508019888796, 'reg_alpha': 0.004813488722819168, 'reg_lambda': 0.0059317875970126 11}. Best is trial 63 with value: 0.3680888792756013.
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Best trial: 63. Best value: 0.368089:  81%|████████  | 81/100 [14:09
<03:23, 10.69s/it]
[I 2025-09-16 20:20:15,128] Trial 80 finished with value: 0.35234537
077102807 and parameters: {'n_estimators': 900, 'learning_rate': 0.1
9733617931739716, 'max_depth': 6, 'subsample': 0.8618976634990771, '
colsample_bytree': 0.6534254627630637, 'gamma': 3.226168689324286e-0
5, 'reg_alpha': 0.19618764148194243, 'reg_lambda': 0.003072217869883
802}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  82%|████████  | 82/100 [14:15
<02:44,  9.13s/it]
[I 2025-09-16 20:20:20,607] Trial 81 finished with value: 0.35948275
905427535 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
24222362826652 9, 'max_depth': 5, 'subsample': 0.7841489815605293, 'c
olsample_bytree': 0.6311834229695459, 'gamma': 0.003823171768073674,
'reg_alpha': 0.008821741170452552, 'reg_lambda': 0.00179007731740312
87}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  83%|████████  | 83/100 [14:19
<02:11,  7.71s/it]
[I 2025-09-16 20:20:25,002] Trial 82 finished with value: 0.35352462
569945947 and parameters: {'n_estimators': 400, 'learning_rate': 0.1
415410852388273, 'max_depth': 5, 'subsample': 0.8290681948743499, 'c
olsample_bytree': 0.6063351244091252, 'gamma': 0.000827105460493229
3, 'reg_alpha': 0.06335092855184482, 'reg_lambda': 0.000964770265329
9419}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  84%|████████  | 84/100 [14:23
<01:46,  6.66s/it]
[I 2025-09-16 20:20:29,208] Trial 83 finished with value: 0.36361649
43161346 and parameters: {'n_estimators': 500, 'learning_rate': 0.24
099670041262597, 'max_depth': 4, 'subsample': 0.8134088137595721, 'c
olsample_bytree': 0.6003112908254035, 'gamma': 0.007682125468459807,
'reg_alpha': 0.014879708224819167, 'reg_lambda': 0.00015739331637424
568}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  85%|████████▌ | 85/100 [14:28
<01:28,  5.93s/it]
[I 2025-09-16 20:20:33,429] Trial 84 finished with value: 0.36681873
468672277 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
4236374439639555, 'max_depth': 4, 'subsample': 0.8114225522950537, '
colsample_bytree': 0.624897745229276, 'gamma': 0.007642226436717594,
'reg_alpha': 0.0125121677271614, 'reg_lambda': 0.0001292782705598323
3}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  86%|████████▌ | 86/100 [14:35
<01:27,  6.28s/it]
[I 2025-09-16 20:20:40,547] Trial 85 finished with value: 0.35703904
15889149 and parameters: {'n_estimators': 1300, 'learning_rate': 0.2
452551061471577, 'max_depth': 3, 'subsample': 0.8933591948331553, 'c
olsample_bytree': 0.6249938898024809, 'gamma': 8.2926388537337e-06,
'reg_alpha': 0.03026776361465968, 'reg_lambda': 0.000149345785530930
97}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  87%|████████▋ | 87/100 [14:39
<01:13,  5.67s/it]
```

```
[I 2025-09-16 20:20:44,786] Trial 86 finished with value: 0.35511060
13947552 and parameters: {'n_estimators': 500, 'learning_rate': 0.26
31600823817096, 'max_depth': 4, 'subsample': 0.8176242099881249, 'co
lsample_bytree': 0.6385516486682805, 'gamma': 0.009554971983589186,
'reg_alpha': 0.1204777006347214, 'reg_lambda': 9.488775777894357e-0
5}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  88%|████████▊ | 88/100 [14:43
<01:01,  5.08s/it]
[I 2025-09-16 20:20:48,505] Trial 87 finished with value: 0.36560143
83013272 and parameters: {'n_estimators': 400, 'learning_rate': 0.27
06296343286879, 'max_depth': 4, 'subsample': 0.8457778599933399, 'co
lsample_bytree': 0.7295570022458029, 'gamma': 0.06494340702218288, '
reg_alpha': 2.1560541010474717e-07, 'reg_lambda': 4.298786310072832e
-06}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  89%|████████▉ | 89/100 [14:46
<00:48,  4.45s/it]
[I 2025-09-16 20:20:51,462] Trial 88 finished with value: 0.34214604
499827556 and parameters: {'n_estimators': 400, 'learning_rate': 0.2
5181119583591116, 'max_depth': 3, 'subsample': 0.8451162524590883, '
colsample_bytree': 0.733532191528526, 'gamma': 0.06875037247788132,
'reg_alpha': 0.0006077154513409054, 'reg_lambda': 5.1299215712645904
e-06}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  90%|█████████ | 90/100 [14:52
<00:51,  5.13s/it]
[I 2025-09-16 20:20:58,188] Trial 89 finished with value: 0.35688020
13727673 and parameters: {'n_estimators': 800, 'learning_rate': 0.27
081414079119653, 'max_depth': 4, 'subsample': 0.7874699064157121, 'c
olsample_bytree': 0.7535612216462397, 'gamma': 0.2676765667970566, '
reg_alpha': 2.2687147956585704e-07, 'reg_lambda': 2.8503944011271142
e-05}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  91%|█████████ | 91/100 [15:01
<00:56,  6.24s/it]
[I 2025-09-16 20:21:07,018] Trial 90 finished with value: 0.35994823
88720527 and parameters: {'n_estimators': 1100, 'learning_rate': 0.2
828846029882484 7, 'max_depth': 4, 'subsample': 0.8291337706493132, '
colsample_bytree': 0.722011924686526, 'gamma': 0.13377943842227377,
'reg_alpha': 2.021267505933394e-08, 'reg_lambda': 1.1471390974290845
e-07}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  92%|█████████▏| 92/100 [15:06
<00:45,  5.70s/it]
[I 2025-09-16 20:21:11,456] Trial 91 finished with value: 0.36217546
12362083 and parameters: {'n_estimators': 500, 'learning_rate': 0.23
1825789466341, 'max_depth': 4, 'subsample': 0.805142802523641 7, 'col
sample_bytree': 0.6192596221924092, 'gamma': 0.04180609405241961, 'r
eg_alpha': 1.4712908841760852e-07, 'reg_lambda': 6.79224107022257e-0
5}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  93%|█████████▎| 93/100 [15:09
<00:34,  4.89s/it]
[I 2025-09-16 20:21:14,458] Trial 92 finished with value: 0.34883719
85469308 and parameters: {'n_estimators': 400, 'learning_rate': 0.25
949480732767943, 'max_depth': 3, 'subsample': 0.7725561490704358, 'c
olsample_bytree': 0.6840710930907491, 'gamma': 0.013033119290068654,
'reg_alpha': 1.1199676930320404e-06, 'reg_lambda': 0.000186922307118
84027}. Best is trial 63 with value: 0.3680888792756013.
```

```
Best trial: 63. Best value: 0.368089:  94%|█████████▍| 94/100 [15:12
<00:26,  4.35s/it]
[I 2025-09-16 20:21:17,536] Trial 93 finished with value: 0.35775123
1838636 and parameters: {'n_estimators': 300, 'learning_rate': 0.238
35514691878187, 'max_depth': 4, 'subsample': 0.8622204150463707, 'co
lsample_bytree': 0.6470565908652233, 'gamma': 0.006592287388079227,
'reg_alpha': 5.764758158987952e-06, 'reg_lambda': 0.0005016404439695
961}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  95%|█████████▌| 95/100 [15:20
<00:27,  5.43s/it]
[I 2025-09-16 20:21:25,499] Trial 94 finished with value: 0.35583519
56827004 and parameters: {'n_estimators': 600, 'learning_rate': 0.21
797864282287033, 'max_depth': 5, 'subsample': 0.8252575874490519, 'c
olsample_bytree': 0.930736016574681, 'gamma': 0.023423979222020705,
'reg_alpha': 3.124993096517401e-05, 'reg_lambda': 0.0003621409316349
1147}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  96%|█████████▌| 96/100 [15:24
<00:20,  5.10s/it]
[I 2025-09-16 20:21:29,833] Trial 95 finished with value: 0.36221618
843285813 and parameters: {'n_estimators': 500, 'learning_rate': 0.2
415496584736025, 'max_depth': 4, 'subsample': 0.7584849165484059, 'c
olsample_bytree': 0.636251016776926, 'gamma': 0.0153351144045587, 'r
eg_alpha': 0.01602910325817692, 'reg_lambda': 6.161551795420431e-0
7}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  97%|█████████▋| 97/100 [15:31
<00:16,  5.52s/it]
[I 2025-09-16 20:21:36,326] Trial 96 finished with value: 0.36181030
662023844 and parameters: {'n_estimators': 600, 'learning_rate': 0.2
4895992876215767, 'max_depth': 5, 'subsample': 0.7979492083820088, '
colsample_bytree': 0.6010356683728886, 'gamma': 0.04990180935063939,
'reg_alpha': 0.8322099385280196, 'reg_lambda': 4.451483356113208e-0
8}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  98%|█████████▊| 98/100 [15:33
<00:09,  4.54s/it]
[I 2025-09-16 20:21:38,568] Trial 97 finished with value: 0.31452441
460921704 and parameters: {'n_estimators': 200, 'learning_rate': 0.2
283313292068819, 'max_depth': 3, 'subsample': 0.606227829354561, 'co
lsample_bytree': 0.7036715816454903, 'gamma': 0.007310514926818485,
'reg_alpha': 0.004006559155680313, 'reg_lambda': 9.203755107474904e-
05}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089:  99%|█████████▉| 99/100 [15:38
<00:04,  4.60s/it]
[I 2025-09-16 20:21:43,322] Trial 98 finished with value: 0.36131695
5051301 and parameters: {'n_estimators': 400, 'learning_rate': 0.273
6515974354586, 'max_depth': 5, 'subsample': 0.8110221638375029, 'col
sample_bytree': 0.67612541763983, 'gamma': 0.0021427715408247464, 'r
eg_alpha': 0.0016057720362509167, 'reg_lambda': 2.166131083398958e-0
6}. Best is trial 63 with value: 0.3680888792756013.
Best trial: 63. Best value: 0.368089: 100%|██████████| 100/100 [15:4
3<00:00,  9.44s/it]
```

```
[I 2025-09-16 20:21:49,011] Trial 99 finished with value: 0.36320222
272541297 and parameters: {'n_estimators': 700, 'learning_rate': 0.2
9194596669893313, 'max_depth': 4, 'subsample': 0.847814910594692, 'c
olsample_bytree': 0.614496182084424, 'gamma': 0.0010043490024121378,
'reg_alpha': 0.024238943532077315, 'reg_lambda': 3.708103682440119e-
05}. Best is trial 63 with value: 0.3680888792756013.

--- Hyperparameter Optimization Complete ---

Best trial:
  Value: 0.3680888792756013
  Params:
    n_estimators: 500
    learning_rate: 0.23070537010502126
    max_depth: 5
    subsample: 0.7799609753789188
    colsample_bytree: 0.6376980598132558
    gamma: 0.004149789577432561
    reg_alpha: 3.39455861552526
    reg_lambda: 0.0005094339148476729
```

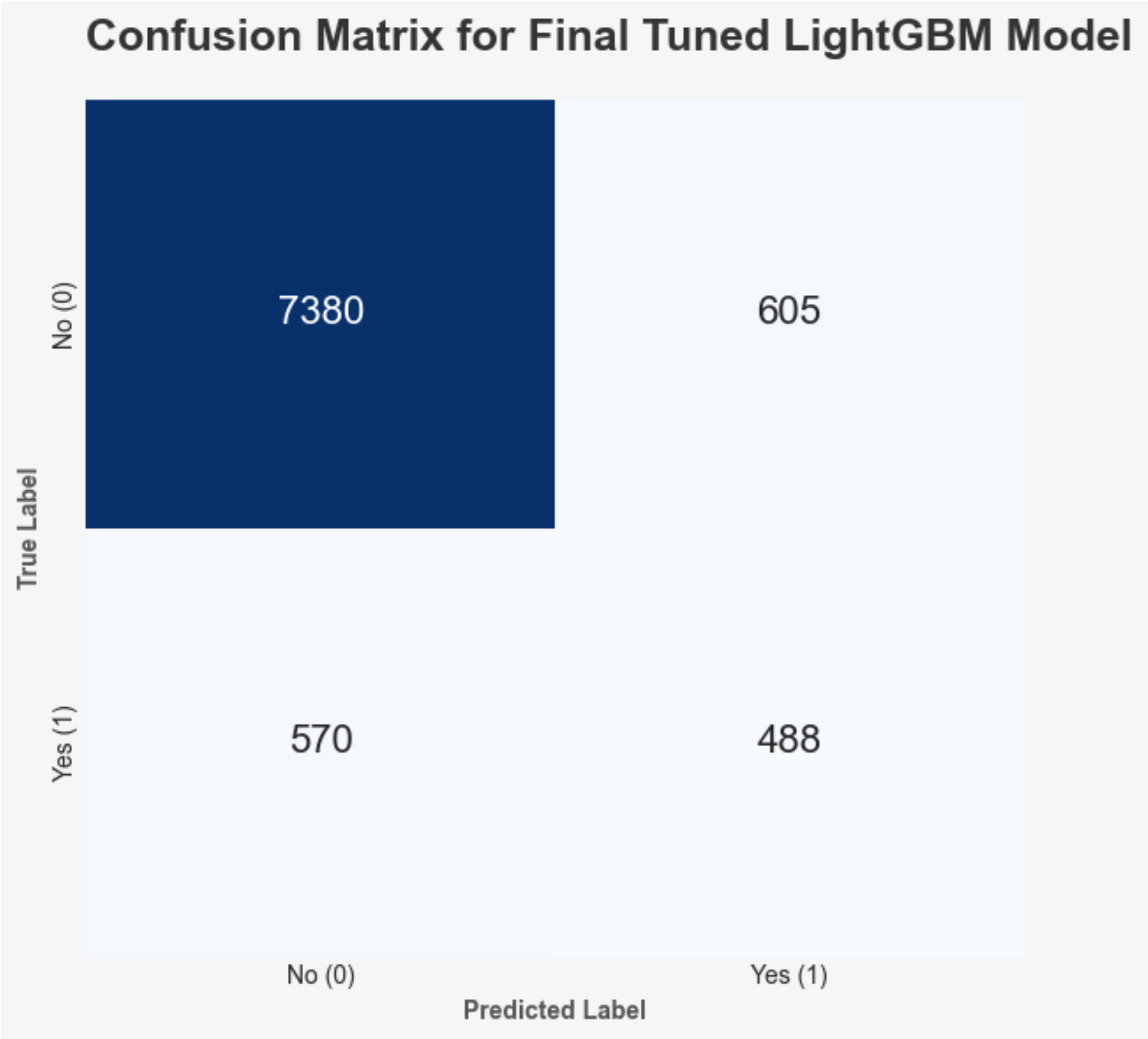
Training Best Model

After running Optuna studies on both LGBM and XGBoost, LGBM yielded the highest F1-Score at ~ `0.45` . We can now build our final pipeline with these hyperparameters and assess performance.

In [71]:
```python
# Retrieving the best set of hyperparameters
best_lgbm_params = study_lgbm.best_params

final_lgbm_model = LGBMClassifier(**best_lgbm_params, random_state=

# Creating the final pipeline with the best LightGBM model
final_pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor_engineered),
    ('smote', SMOTE(random_state=seed)),
    ('classifier', final_lgbm_model)
])

# Training the final model
print("\n--- Training Final LightGBM Model with Optimized Hyperpara
start_time = time.time()
final_pipeline.fit(X_train, y_train)
end_time = time.time()
training_time = end_time - start_time
print(f"Final LightGBM model trained in {training_time:.2f} seconds
y_pred_final = final_pipeline.predict(X_test)
y_proba_final = final_pipeline.predict_proba(X_test)[:, 1]

# Evaluating the final model
print("\n--- Final Model Evaluation ---\n")
print("Classification Report:\n")
print(classification_report(y_test, y_pred_final, target_names=['no
plot_confusion_matrix(y_test, y_pred_final, "Final Tuned LightGBM M
```

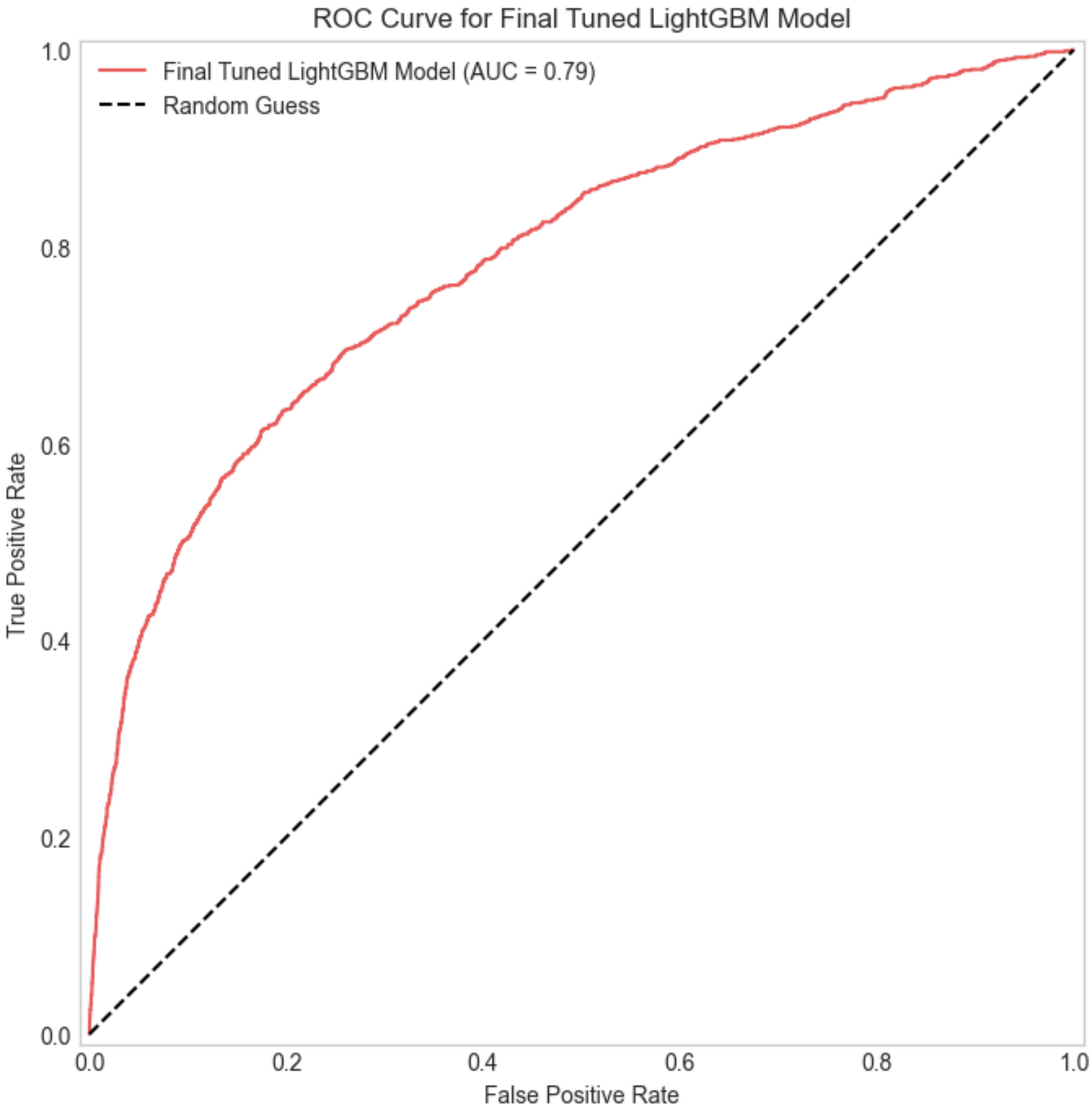
```
final_metrics = {
    'Precision': precision_score(y_test, y_pred_final),
    'Recall': recall_score(y_test, y_pred_final),
    'F1-Score': f1_score(y_test, y_pred_final),
    'ROC AUC': roc_auc_score(y_test, y_proba_final),
    'Training Time (s)': training_time
}
final_resutls_df = pd.DataFrame([final_metrics], index=['Final Tune
print("\nFinal Model Performance:\n")
display(final_resutls_df.style.format({'Precision': '{:.2f}', 'Reca
                                       'ROC AUC': '{:.2f}', 'Traini
# Plotting ROC Curve for the final model
fig, ax = plt.subplots(figsize=(8, 8))
RocCurveDisplay.from_predictions(y_test, y_proba_final, name="Final
ax.plot([0, 1], [0, 1], 'k--', label='Random Guess')
ax.set_title('ROC Curve for Final Tuned LightGBM Model')
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.legend()
plt.grid()
plt.show()
```

```
--- Training Final LightGBM Model with Optimized Hyperparameters ---

Final LightGBM model trained in 6.37 seconds.

--- Final Model Evaluation ---

Classification Report:

              precision    recall  f1-score   support

          no       0.93      0.92      0.93      7985
         yes       0.45      0.46      0.45      1058

    accuracy                           0.87      9043
   macro avg       0.69      0.69      0.69      9043
weighted avg       0.87      0.87      0.87      9043
```




```
Final Model Performance:
```

	Precision	Recall	F1-Score	ROC AUC	Training Time (s)
Final Tuned LightGBM Model	0.45	0.46	0.45	0.79	6.37



The fine-tuned LightGBM model achieved a strong performance on the hold-out test set, with an F1-Score of `0.45` and a ROC AUC of `0.79`. When compared to our best untuned model, the `GradientBoostingClassifier`, the results are very competitive. The untuned Gradient Boosting model also achieved an F1-Score of 0.45 but with a different performance profile.

The confusion matrices reveal that:

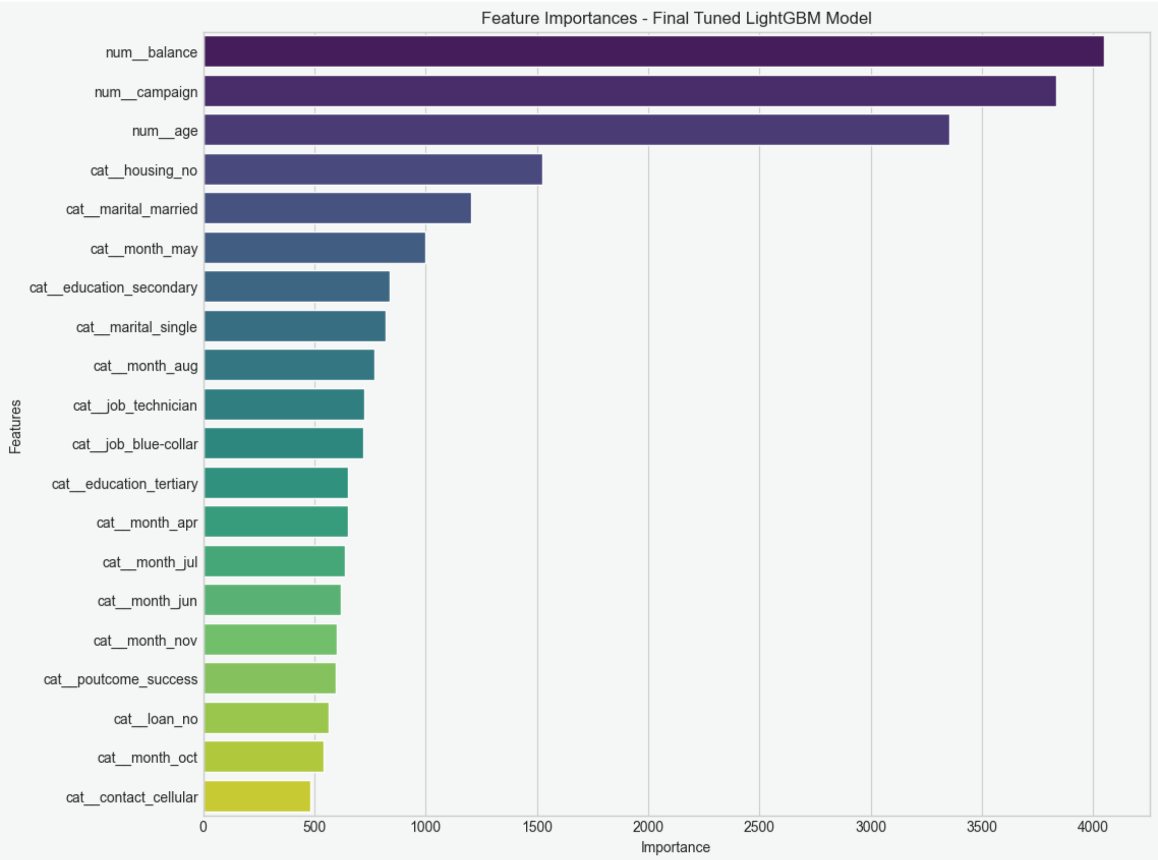
- Our fine-tuned LightGBM is more **precise** (0.45 vs. 0.42), making fewer false positive errors.
- The Gradient Boosting model, on the other hand, had a slightly higher **Recall**, identifying more potential subscribers but at the cost of more wasted calls.

Given that the fine-tuned LightGBM models achieves a top-tier F1-score, has better precision, a superior ROC AUC for ranking leads, and is significantly more **computationally efficient**, we select it as our final model. It gives us the best combination of predictive power and practical usability for this business problem.

Feature Importance

Now that we have a final model, the last step is to check its behavior. In this section, we will visualize feature importances from our fined-tuned LGBM model. The goal is to understand which data points are most influentional in its decision-making.

In [ ]:
```
# Computing Feature Importance
importances = final_pipeline.named_steps['classifier'].feature_impo
feature_names = final_pipeline.named_steps['preprocessor'].get_feat
feature_importances = pd.Series(importances, index=feature_names).s

# Plotting Feature Importances
plt.style.use('seaborn-v0_8-whitegrid')
fig,ax = plt.subplots(figsize=(12,10))
fig.set_facecolor('#f5f7f6')
ax.set_facecolor('#f5f7f6')

sns.barplot(x=feature_importances, y=feature_importances.index, ax=
ax.set_title('Feature Importances - Final Tuned LightGBM Model')
ax.set_xlabel('Importance')
ax.set_ylabel('Features')
plt.show()
```



- **Client Financial Profile**
  - The client's financial profile appears to be the most dominant factor in the model's predictions. `balance` is the top feature. We can also see that the model is also considering whether the client has an existing `housing` or `personal loan`. This strongly supports our hypothesis that clients with fewer existing financial liabilities are the primary target audience.
- **Campaign Strategy & Timing**
  - The `campaign` itself, specifically the number of contacts, is the second most important predictor, reinforcing that an optimized contact strategy is crucial. The **timing** of the campaign is also highly influential, with `month_may` (our least successful month) being a top predictor, alongside several other months. The outcome of a previous campaign (`poutcome_success`) also remains a key indicator.
- **Client Demographics**
  - `Age` is the third most powerful feature overall. Other demographic details like `marital` status, `education` level, and `job` type also contribute significantly to the model's predictions, allowing it to build a profile of likely subscribers.

Saving Model

The final step is to save our trained model so it can be used in other applications. We'll use the joblib library to serialize our entire `final_pipeline` object to a file. Saving the complete pipeline is crucial, as it ensures the exact same preprocessing steps are applied to new data during prediction, guaranteeing consistent results. This file can then be loaded to make live predictions without needing to retrain the model.

In [ ]:
```
# Displaying final pipeline
final_pipeline
```

Out[ ]:

```
▸ Pipeline
  ▸ preprocessor: ColumnTransformer
    ▸ cat                                  ▸
      ▾ OneHotEncoder                      ▾ PowerTra
        ▾ Parameters                         ▾ Parameter
```

	categories	'auto'
	drop	None
	sparse_output	True
	dtype	<class 'numpy.float64'>
	handle_unknown	'ignore'
	min_frequency	None
	max_categories	None
	feature_name_combiner	'concat'

	met
	standard
	c

SMOTE

▾ Parameters

	sampling_strategy	'auto'
	random_state	42
	k_neighbors	5

LGBMClassifier

▾ Parameters

	boosting_type	'gbdt'
	num_leaves	1440
	max_depth	10
	learning_rate	0.01032565119154107
	n_estimators	200
	subsample_for_bin	200000
	objective	None
	class_weight	None
	min_split_gain	0.0
	min_child_weight	0.001
	min_child_samples	45
	subsample	0.9643946012301383
	subsample_freq	0

subsample_freq	0
colsample_bytree	0.8979866059177901
reg_alpha	1.2879201869482782e-08
reg_lambda	2.74426603318653e-06
random_state	42
n_jobs	-1
importance_type	'split'
verbose	-1

In [74]:
```
# Saving model
model_dir = '../models'
file_name = 'final_lgbm_pipeline.joblib'
file_path = os.path.join(model_dir, file_name)

os.makedirs(model_dir, exist_ok=True)
joblib.dump(final_pipeline, file_path)

print(f"\nModel saved to {file_path}")
```

```
Model saved to ../models/final_lgbm_pipeline.joblib
```

Conclusion

We have successfully developed a machine learning model to improve the efficiency of a bank's telemarketing campaigns. We followed a Data Science workflow, beginning with an Exploratory Data Analysis, then moving on to Data Pipeline & Preprocessing, and finally Model Selection and Fine-Tuning.

Our final model, a fine-tuned LightGBM Classifier, achieved a F1-Score of 0.45 and a ROC AUC of 0.79 on the hold-out test set. This represents an improvement over our baseline and provides the bank with a tool to identify and prioritize high-potential clients.

Our analysis confirmed the critical importance of campaign timing, client demographic (age, job), and financial profile (balance, existing loans). With these patterns, the final model can help the bank focus its resources more effectively, reducing costs associated with contacting uninterested clients, and ultimately increase its term deposit subscription rate. The saved pipeline is now ready for deployment in a production environment or an interactive application.
