Title : Predicting Term Deposit Subscriptions using Machine Learning

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Project Goal: Build a machine learning model to predict whether a bank client will subscribe to a term deposit based on their profile and past interactions. The objective is to support marketing efforts by identifying likely subscribers ahead of time.

This end-to-end project includes data cleaning, exploratory data analysis (EDA), feature engineering, handling class imbalance, training multiple models, hyperparameter tuning, and evaluation using real-world metrics.
The dataset is highly imbalanced and reflects a realistic marketing problem faced by financial institutions

Introduction

This notebook covers:

- Data loading and cleaning
- Exploratory Data Analysis (EDA)
- Feature engineering and preprocessing
- Handling imbalanced data using SMOTE
- Model training and evaluation (Logistic Regression, Random Forest, Gradient Boosting, XGBoost)
- Visualizations and performance comparisons

Dataset: UCI Bank Marketing Dataset (https://archive.ics.uci.edu/dataset/222/bank+marketing)

Importing Libraries

In [6]:
```
import pandas as pnd                                    # For Data Loading and Exploration
import numpy as npy                                     # For Numerical Operations
import matplotlib.pyplot as mplt                        # For Data Visualisation
import seaborn as sea                                   # For Data Visualisation

from sklearn.model_selection import train_test_split    # For Spliting dataset

from sklearn.preprocessing import StandardScaler        # For Standardising the Numerical Values
from sklearn.preprocessing import LabelEncoder          # For Converting Categorical Variables in to Numerical Values

from imblearn.over_sampling import SMOTE                # For SMOTE Technique

from sklearn.linear_model import LogisticRegression     # For LR Model
from sklearn.ensemble import RandomForestClassifier     # For RF Model
from sklearn.ensemble import GradientBoostingClassifier # For GB Model
import xgboost as xgb                                   # For XGB Model

from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier

#Imports for Evaluation
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import RocCurveDisplay
from sklearn.metrics import precision_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import PrecisionRecallDisplay
from sklearn.metrics import f1_score

from IPython.display import display

import os                                              # For Interacting with Operating System such as to create folders etc
import re                                              # For Regular expressions usage

# For Surpassing non crital warnings
import warnings
warnings.filterwarnings('ignore')

# For Setting the random seed for reproducibility
npy.random.seed(42)
```

Dataset Overview

I have used the Bank Marketing dataset from the UCI repository. It contains information about 45,211 marketing campaigns.

- 16 input variables: age, job, marital status, education, contact type, previous outcomes, etc.
- 1 target variable: `y` — whether the client subscribed to a term deposit.

First, I will load and inspect the dataset:

Loading the Data

In [9]:
```
def loading_the_csv_dataset(filepath):
    """
    This function loads the csv data
    """
    try:
        df = pnd.read_csv(filepath, encoding='utf-8', delimiter=';')
        print("Data loaded successfully. Shape:", df.shape)
        print("\n")
        info = df.info()
        display(info)
        print("\n")
        head = df.head(5)
        display(head)
```

```python
        return df
    except FileNotFoundError:
        print(f"File not found. Please make sure ---- '{filepath}' ---- exists.")
        return None
    except pnd.errors.ParserError:
        print(f"Failed to parse '{filepath}'. Please check the file format.")
        return None
```

Data Cleaning

I will clean the data by cleaing column names, remove duplicates, and handle missing or placeholder values (`'unknown'` , `'NA'` , etc.). For categorical features, we replace `'unknown'` with the mode.

Cleaning the Dataset

In [12]:
```python
def basic_cleaning_of_the_dataset(df):
    """
    This function clean the dataset
    """
    df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')                    # Cleaning the column names
    df.columns = df.columns.map(lambda x: re.sub(r'\W+', '_', x))
    df = df.loc[:, ~df.columns.str.contains('^unnamed')]                                      # Removing the unnamed Column
    df = df.drop_duplicates()                                                                 # Droping the duplicates
    df = df.apply(lambda x: x.str.strip() if x.dtype == "object" else x)                      # Removing the whitespaces from data

    missing_placeholders = ['', 'NA', 'null', '-', 'N/A']
    found_any = False
    print("\n")
    for placeholder in missing_placeholders:
        count = (df == placeholder).sum().sum()
        if count > 0:
            print(f"Replacing {count} '{placeholder}' values with pd.NA")
            found_any = True
    if not found_any:
        print(f"There are no Null Values ")
    df.replace(missing_placeholders, pnd.NA, inplace=True)                                    # Replacing missing values with NA

    categorical_cols = df.select_dtypes(include=['object']).columns                           # Replacing the Value "Unkonwn" with mode value
    print("\n")
    for col in categorical_cols:
        if 'unknown' in df[col].values:
            count = (df[col] == 'unknown').sum()
            mode_value = df[col][df[col] != 'unknown'].mode()[0]
            df[col] = df[col].replace('unknown', mode_value)
            print(f"Replacing {count} 'unknown' values in '{col}' with mode: '{mode_value}'")
    return df
```

Exploratory Data Analysis (EDA)

Next, I will examine the distribution of the target variable and features, identify outliers, and understand relationships between variables.

EDA - Exploratory Data Analysis

In [15]:
```python
def summary_stats(df):
    """
    This function will generate summary stats
    """
    print("\nSummary Statistics:")
    stats = df.describe(include='all').round(2)                                                          # Basic Statistics
    display(stats)
```

In [16]:
```python
def target_distribution(df, target_var):
    """
    This function will generate class distribution count and distribution chart of target variable
    """
    print("\n" + "="*30)
    print("EDA: Distribution of Target Variable (Subscription to Term Deposit)")
    print("="*30 + "\n")

    print("Value Counts:\n", df[target_var].value_counts())
    print("Class Proportions:\n", df[target_var].value_counts(normalize=True).round(3)*100)

    mplt.figure(figsize=(8, 6))                                                                 # Distribution of target variable
    sea.countplot(x=target_var, data=df)
    mplt.title('Distribution of Target Variable (Subscription to Term Deposit)')
    mplt.xlabel('Subscription')
    mplt.ylabel('Count')
    mplt.savefig('plots/eda/target_distribution.png')
    #mplt.show()
    mplt.close()
```

In [17]:
```python
def histogram_for_numeric_values(df, numeric_cols):
    """
    This function will generate histograms of numeric values
    """

    print("\n" + "="*30)
    print("EDA: Histogram of Numeric Features")
    print("="*30 + "\n")

    n_cols = 2                                                                       # Histograms for understanding features
    n_rows = int(npy.ceil(len(numeric_cols) / n_cols))


    fig, axes = mplt.subplots(n_rows, n_cols, figsize=(n_cols * 5, n_rows * 4))
    axes = axes.flatten()

    for i, col in enumerate(numeric_cols):
        sea.histplot(df[col], bins=30, kde=True, ax=axes[i], color='skyblue')
        axes[i].set_title(f'Distribution of {col}')

    for j in range(i + 1, len(axes)):
        axes[j].axis('off')
```

```python
    mplt.tight_layout()
    mplt.savefig("plots/eda/histogram.png")
    mplt.show()
```

In [18]:
```python
def boxplots_for_numeric_values_and_target(df, numeric_cols, target_val):
    """
    This function will generate boxplots of numeric values and target variable
    """

    print("\n" + "="*30)
    print("EDA: Boxplots of Numeric Features")
    print("="*30 + "\n")

    n_cols = 2                                                              # Box Plots for understanding relationship with target
    n_rows = int(npy.ceil(len(numeric_cols) / n_cols))


    fig, axes = mplt.subplots(n_rows, n_cols, figsize=(n_cols * 5, n_rows * 4))
    axes = axes.flatten()

    for i, col in enumerate(numeric_cols):
        sea.boxplot(x=target_val, y=col, data=df, ax=axes[i], color='red')
        axes[i].set_title(f'{col} vs {target_val}')
        axes[i].set_xlabel(target_val)
        axes[i].set_ylabel(col)

    for j in range(i + 1, len(axes)):
        axes[j].axis('off')

    mplt.tight_layout()
    mplt.savefig("plots/eda/Boxplot.png")
    mplt.show()
```

In [19]:
```python
def countplots_for_categorical_values_and_target(df, categorical_cols, target_val):
    """
    This function will generate countplots of numeric valuesand target variable
    """

    print("\n" + "="*30)
    print("EDA: Countplots of Categorical Features")
    print("="*30 + "\n")

    n_cols = 4                                                             # Count Plots for understanding distribution with target
    n_rows = int(npy.ceil(len(categorical_cols) / n_cols))


    fig, axes = mplt.subplots(n_rows, n_cols, figsize=(n_cols * 5, n_rows * 4))
    axes = axes.flatten()

    for i, col in enumerate(categorical_cols):
        sea.countplot(x=col, hue=target_val, data=df, ax=axes[i], palette='pastel')
        axes[i].set_title(f'{col} distribution by {target_val}')
        axes[i].set_xlabel(target_val)
        axes[i].tick_params(axis='x', rotation=45)
        axes[i].set_ylabel(col)

    for j in range(i + 1, len(axes)):
        axes[j].axis('off')

    mplt.tight_layout()
    mplt.savefig("plots/eda/countplot.png")
    mplt.show()
```

In [20]:
```python
def visualization_and_eda(df):
    """
    This function will generate the directory "polts" and will call all EDA related Functions
    """

    os.makedirs('plots', exist_ok=True)                                                   # Creating a plots folder if unavailable
    summary_stats(df)

    target_feature = "y"
    target_distribution(df, target_feature)

    numerical_feature = ['age', 'balance', 'pdays',"campaign"]
    histogram_for_numeric_values(df, numerical_feature)
    boxplots_for_numeric_values_and_target(df, numerical_feature, target_feature)


    categorial_feature = ['job', 'marital', 'education', 'housing', 'loan', 'contact', 'poutcome', 'month']
    countplots_for_categorical_values_and_target(df, categorial_feature, target_feature)
    #return df
```

Feature Engineering and Preprocessing

Further, I am plaing to create new features to capture interaction effects and improve predictive power:

- `housing_loan` : combines housing and loan status
- `contact_frequency` : ratio of campaign to `pdays`
- `success_ratio` : past success over campaigns

I will also apply

- log transformation to skewed numerical features.
- Label encoding of categorical variables
- Scaling of numerical features using `StandardScaler`
- Outlier clipping based on IQR method

Data Preprocessing

```
In [23]: def bank_dataset_preprocessing(df):
    """
    This function will be specfic to the dataset and have adopted preprocessing steps
    """
    df = df.drop(columns=['duration']) # Droping the duration column as these column information not available during prediction
    df = df.drop(columns=['day'])      #Droping day column as its of no use in my project objective

    df['y'] = df['y'].map({'yes': 1, 'no': 0}) # Converting Target Variable to Binary

    df['pdays'] = df['pdays'].replace(-1, 999)  # Replacing pdays value from -1 to 999 for better feature transformation


    for col in ['balance','age', 'campaign', 'previous', 'pdays']:                           # Handeling Outliers
            q1 = df[col].quantile(0.25)
            q3 = df[col].quantile(0.75)
            iqr = q3 - q1
            upper_bound = q3 + 1.5 * iqr
            df[col] = df[col].clip(upper=upper_bound)

    #Interaction feature of housing and loan for capturing combined effect
    df['housing_loan'] = df['housing'].astype(str) + "_" + df['loan'].astype(str)

    df['contact_frequency'] = df['campaign'].astype(float) / (df['pdays'] + 1).astype(float)  #Feature engineering: create contact frequency ratio
    df['success_ratio'] = df['previous'].astype(float) / (df['campaign'] + 1).astype(float)   #Feature engineering: create success ratio

    numeric_cols = df.select_dtypes(include=['int64']).drop(columns=['y']).columns            #Checking for Skewness in numeric columns
    skewed_cols = df[numeric_cols].skew().sort_values(ascending=False)
    print("\n")
    for col, skew in skewed_cols.items():
        if skew > 1:
            df[col] = npy.log1p(df[col].clip(lower=0))                                        # Applying log transformation if there is skewness
            print(f"Log Transformation Applied to '{col}' (skewness={skew:.2f})")

    categorical_cols = df.select_dtypes(include=['object']).columns                           # Encoding Categorical Variables using LabelEncoder
    le = LabelEncoder()
    for col in categorical_cols:
        df[col] = le.fit_transform(df[col])

    print("\n")
    print("Dataset Shape after preprocessing:", df.shape)
    print("Any Missing Values After Preprocessing..? and have ", df.isnull().sum())
    return df
```

```
In [24]: def correlation_analysis(df):
    """
    This function will analyse the relationship between features
    """

    print("\n" + "="*30)
    print("Heat Map: Correlation analysis")
    print("="*30 + "\n")

    mplt.figure(figsize=(10, 8))
    corr_var = df.corr(numeric_only=True)
    sea.heatmap(corr_var, annot=True, fmt='.2f', cmap='coolwarm', square=True)
    mplt.title('Correlation analysis using Heatmap')
    mplt.savefig("plots/eda/Heatmap -  Correlation Analysis.png")
    mplt.show()
```

Baseline Model Evaluation

I will be training and evaluate the following models:

- Logistic Regression
- Random Forest
- Gradient Boosting
- XGBoost

Metrics will be using: Accuracy, Precision, Recall, F1-Score, ROC AUC

Modeling Functions

Splitting Features and Target Function

```
In [28]: def splitting_features_and_target(df,target_var):
    """
    This function will split the X and Y Variables
    """

    Features = df.drop(target_var, axis=1)
    Target = df[target_var]
    print("Shape of the Features:", Features.shape)
    print("Shape of the Target:", Target.shape)
    return Features, Target
```

Splitting the data set for training, validation and testing

```
In [30]: def splitting_dataset(x, y, test_size):
    """
    This function will split the dataset in desired size
    """

    X_train, X_test, y_train, y_test = train_test_split( x, y, test_size=test_size, random_state=42, stratify=y)
    return X_train, X_test, y_train, y_test
```

Applying SMOTE Technique

```
In [32]: def applying_smote_technique(X, y):
    """
    This function will apply SMOTE for class imbalance
    """
    smote = SMOTE(random_state=42)
```

```python
    X_res, y_res = smote.fit_resample(X, y)
    print("\n Distribution of class afte balancing using SMOTE:")
    print(pnd.Series(y_res).value_counts())
    return X_res, y_res
```

In [33]:
```python
def scaling_feature(features_train, features_val, features_test):
    """
    This function will apply Standard Scalar Techniques for features
    """
    scaler = StandardScaler()
    scalar_feature_train = scaler.fit_transform(features_train)
    scalar_feature_val = scaler.transform(features_val)
    scalar_feature_test = scaler.transform(features_test)

    return scalar_feature_train, scalar_feature_val, scalar_feature_test
```

Training and Evaluating model

In [35]:
```python
def model_training_and_evaluation(model, train_features, train_target, val_features, val_target, model_name="Model"):
    """
    This function will Trains and evaluates the desired classification model.
    """


    model.fit(train_features, train_target)
    y_pred = model.predict(val_features)
    y_pred_proba = model.predict_proba(val_features)[:, 1]

    """print("\n" + "="*30)
    print(f"\n {model_name} -- Evaluation Metrics ")
    print("="*30 + "\n")
    print("Confusion Matrix:\n", confusion_matrix(val_target, y_pred))
    print("Classification Report:\n", classification_report(val_target, y_pred))
    print("Accuracy:", accuracy_score(val_target, y_pred))
    print("Precision:", precision_score(val_target, y_pred))
    print("Recall    :", recall_score(val_target, y_pred))
    print("F1 Score :", f1_score(val_target, y_pred))
    print("ROC AUC  :", roc_auc_score(val_target, y_pred_proba))"""

    # Confusion Matrix
    disp = ConfusionMatrixDisplay.from_predictions(val_target, y_pred)
    disp.ax_.set_title(f'{model_name} - Confusion Matrix')
    mplt.savefig(f"plots/evaluation/{model_name}_confusion_matrix.png")
    mplt.close()

    # ROC Curve
    RocCurveDisplay.from_predictions(val_target, y_pred_proba)
    mplt.title(f'{model_name} - ROC Curve')
    mplt.savefig(f"plots/evaluation/{model_name}_roc_curve.png")
    mplt.close()

    # Precision-Recall Curve
    PrecisionRecallDisplay.from_predictions(val_target, y_pred_proba)
    mplt.title(f'{model_name} - Precision Recall Curve')
    mplt.savefig(f"plots/evaluation/{model_name}_pr_curve.png")
    mplt.close()

    return model
```

In [36]:
```python
def feature_importance_chart(model, feature_names, model_name):
    """
    This function will Plots and saves feature importance for tree-based models i.e Random Forest, Gradient Boosting, XGBoost.
    """
    if hasattr(model, 'feature_importances_'):
        importances = model.feature_importances_
        indices = npy.argsort(importances)[::-1]

        mplt.figure(figsize=(6, 4))
        mplt.title(f'{model_name} - Feature Importance')
        sea.barplot(x=importances[indices], y=npy.array(feature_names)[indices])
        mplt.tight_layout()
        mplt.savefig(f"plots/evaluation/{model_name}_feature_importance.png")
        mplt.show()
```

I will split the dataset into:

- **Train set** (64%)
- **Validation set** (16%)
- **Test set** (20%)

In [37]:
```python
def modeling_function(df):
    """
    This function will call all Modeling related Functions
    """
    target_variable = "y"
    X, y = splitting_features_and_target(df,target_variable)


    X_train_val, X_test, y_train_val, y_test = splitting_dataset(X, y, test_size=0.2)             #  Splitting: 80% train+val, 20% test
    X_train, X_val, y_train, y_val = splitting_dataset(X_train_val, y_train_val, test_size=0.2)   # Second split: 20% of train_val goes to validation
    print("\n")
    print("Shape of Train dataset:", X_train.shape)
    print("Shape of Validation dataset:", X_val.shape)
    print("Shape of Test dataset:", X_test.shape)

    X_train_balanced, y_train_balanced = applying_smote_technique(X_train, y_train)

    X_train_balanced_scaled, X_val_scaled, X_test_scaled = scaling_feature(X_train_balanced, X_val, X_test)


    models = {
        'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000),
        'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
        'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, random_state=42),
        'XGBoost': xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
    }
```

```
    evaluation_results = {}

    for name, model in models.items():
        trained_model = model_training_and_evaluation(model, X_train_balanced_scaled, y_train_balanced, X_val_scaled, y_val, model_name=name)

        y_val_pred = trained_model.predict(X_val_scaled)
        y_val_proba = trained_model.predict_proba(X_val_scaled)[:, 1]

        evaluation_results[name] = {
            "model": trained_model,
            "roc_auc": roc_auc_score(y_val, y_val_proba),
            "classification_report": classification_report(y_val, y_val_pred, output_dict=True)
        }
        feature_importance_chart(model, X_train_balanced.columns, model_name=name)

    metrics_list = []

    for model_name, results in evaluation_results.items():
        report = results["classification_report"]
        metrics_list.append({
            "Model": model_name,
            "Accuracy": accuracy_score(y_val, results["model"].predict(X_val_scaled)),
            "Precision": report["1"]["precision"],
            "Recall": report["1"]["recall"],
            "F1 Score": report["1"]["f1-score"],
            "ROC AUC": results["roc_auc"]
        })

    results_df = pnd.DataFrame(metrics_list)
    results_df = results_df.round(3)
    display(results_df)


    mplt.figure(figsize=(6, 4))
    sea.barplot(x="Model", y="ROC AUC", data=results_df)
    mplt.title("Model ROC AUC Comparison", fontsize=16)
    mplt.xlabel("Model", fontsize=12)
    mplt.ylabel("ROC AUC", fontsize=12)
    mplt.xticks(rotation=30)
    mplt.tight_layout()
    mplt.show()



    return {
        "X_train": X_train_balanced_scaled,
        "y_train": y_train_balanced,
        "X_val": X_val_scaled,
        "y_val": y_val,
        "X_test": X_test_scaled,
        "y_test": y_test,
        "baseline_results": evaluation_results
    }
```

Hyperparameter Tuning

I will use GridSearchCV to tune:

- Gradient Boosting
- XGBoost

Best parameters are selected based on ROC AUC score.

Hypertuning the best models

In [40]:
```
def tune_gradient_boosting(X, y):
    param_grid = {
        'n_estimators': [100, 200],
        'max_depth': [3, 5, 7],
        'learning_rate': [0.01, 0.1, 0.2],
        'subsample': [0.8, 1.0]
    }

    gb_model = GradientBoostingClassifier(random_state=42)

    grid_search = GridSearchCV(
        estimator=gb_model,
        param_grid=param_grid,
        scoring='roc_auc',
        cv=3,
        verbose=1,
        n_jobs=-1
    )

    grid_search.fit(X, y)
    print("\n\nBest Gradient Boosting Parameters:")
    print(grid_search.best_params_)
    print(f"ROC AUC (CV): {grid_search.best_score_:.4f}")

    return grid_search.best_estimator_
```

In [41]:
```
def tune_xgboost(X, y):
    param_grid = {
        'n_estimators': [100, 200],
        'max_depth': [3, 5, 7],
        'learning_rate': [0.01, 0.1, 0.2],
        'subsample': [0.8, 1.0]
    }

    xgb_model = xgb.XGBClassifier(
        eval_metric='logloss',
        random_state=42
    )

    grid_search = GridSearchCV(
        estimator=xgb_model,
        param_grid=param_grid,
```

```
        scoring='roc_auc',
        cv=3,
        verbose=1,
        n_jobs=-1
    )

    grid_search.fit(X, y)
    print("\n\nBest XGBoost Parameters:")
    print(grid_search.best_params_)
    print(f"ROC AUC (CV): {grid_search.best_score_:.4f}")

    return grid_search.best_estimator_
```

In [42]:
```
def hypertuning_function(X_train, y_train, X_val, y_val, X_test, y_test):
    """
    This function will call all Modeling related Functions after tuning the hyper parameters or finding the best parameters
    """

    best_xgb_model = tune_xgboost(X_train, y_train)
    best_gb_model = tune_gradient_boosting(X_train, y_train)

    results = {}
    for model, name in zip([best_xgb_model, best_gb_model], ["XGBoost Tuned", "Gradient Boosting Tuned"]):
        model_training_and_evaluation(model, X_train, y_train, X_val, y_val, model_name=name)
        y_val_pred = model.predict(X_val)
        y_val_proba = model.predict_proba(X_val)[:, 1]
        results[name] = {
            "model": model,
            "roc_auc": roc_auc_score(y_val, y_val_proba),
            "classification_report": classification_report(y_val, y_val_pred, output_dict=True)
        }

        os.makedirs("plots/final_evaluation", exist_ok=True)
        disp = ConfusionMatrixDisplay.from_predictions(y_val, y_val_pred)
        disp.ax_.set_title(f'{name} - Test Confusion Matrix')
        mplt.savefig(f"plots/final_evaluation/{name}_test_confusion_matrix.png")
        mplt.close()
    return results
```

Final Evaluation on Unseen Dataset

In [44]:
```
def hypertuned_model_evaluation(models, X_test, y_test):
    print("\nFinal Evaluation on Test Set")
    for name, model in models.items():
        y_test_pred = model.predict(X_test)
        y_proba = model.predict_proba(X_test)[:, 1]


        os.makedirs("plots/final_evaluation", exist_ok=True)
        disp = ConfusionMatrixDisplay.from_predictions(y_test, y_test_pred)
        disp.ax_.set_title(f'{name} - Test Confusion Matrix')
        mplt.savefig(f"plots/final_evaluation/{name}_test_confusion_matrix.png")
        mplt.close()

        print(f"\n{name} - Test ROC AUC: {roc_auc_score(y_test, y_proba):.4f}")
        print(classification_report(y_test, y_test_pred))
```

Main Function

In [46]:
```
file_name = 'bank-full.csv'
file_path = os.path.join('dataset', file_name)
def main():
    """
    This function is the main function
    """
    df_orginal = loading_the_csv_dataset(file_path)
    if df_orginal is None:
        return
    cleaned_df = basic_cleaning_of_the_dataset(df_orginal.copy())
    visualization_and_eda(cleaned_df)
    processed_df = bank_dataset_preprocessing(cleaned_df.copy())
    correlation_analysis(processed_df)
    results = modeling_function(processed_df.copy())
    tuned_results = hypertuning_function(
                                        results["X_train"], results["y_train"],
                                        results["X_val"], results["y_val"],
                                        results["X_test"], results["y_test"]
                                    )
    hypertuned_model_evaluation(
        {name: result["model"] for name, result in tuned_results.items()},
        results["X_test"], results["y_test"]
    )

# Commented out main function call for notebook-style, step-by-step execution.


#if __name__ == "__main__":
#    main()
```

#Note:

The full pipeline is originally designed to run in one step using the `main()` function. In the above cell I have Commented out main function call.

But, For the purpose of this notebook readability, exploration, and markdown explanation.

I will now run each step separately below. This helps me visualize intermediate outputs like EDA plots and model evaluation results.

Load Dataset

I will load the Bank Marketing dataset which contains 45,211 rows and 17 columns. Below is a preview and a summary of the dataset structure.

```
In [50]: file_name = 'bank-full.csv'
         file_path = os.path.join('dataset', file_name)
         df_orginal = loading_the_csv_dataset(file_path)
```

```
Data loaded successfully. Shape: (45211, 17)


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
None
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

Basic Cleaning

```
In [52]: cleaned_df = basic_cleaning_of_the_dataset(df_orginal.copy())
```

```
There are no Null Values


Replacing 288 'unknown' values in 'job' with mode: 'blue-collar'
Replacing 1857 'unknown' values in 'education' with mode: 'secondary'
Replacing 13020 'unknown' values in 'contact' with mode: 'cellular'
Replacing 36959 'unknown' values in 'poutcome' with mode: 'failure'
```

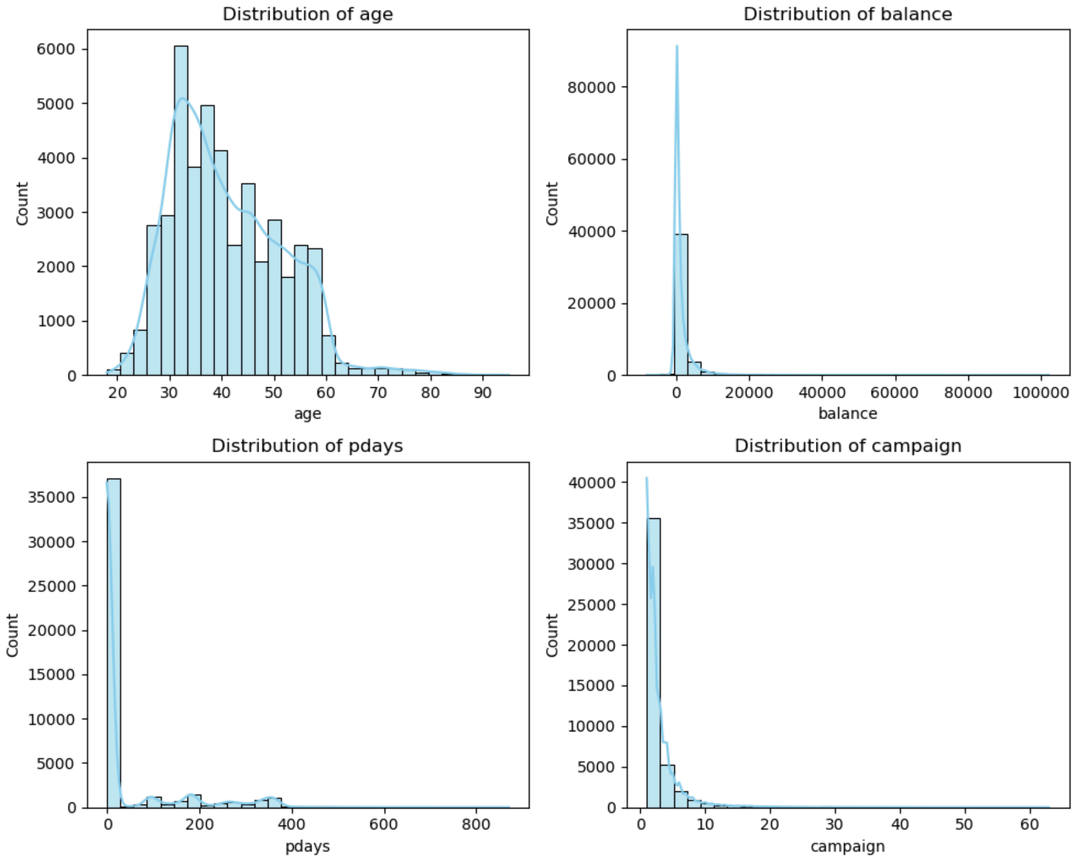
Exploratory Data Analysis (EDA)

```
In [54]: visualization_and_eda(cleaned_df)
```

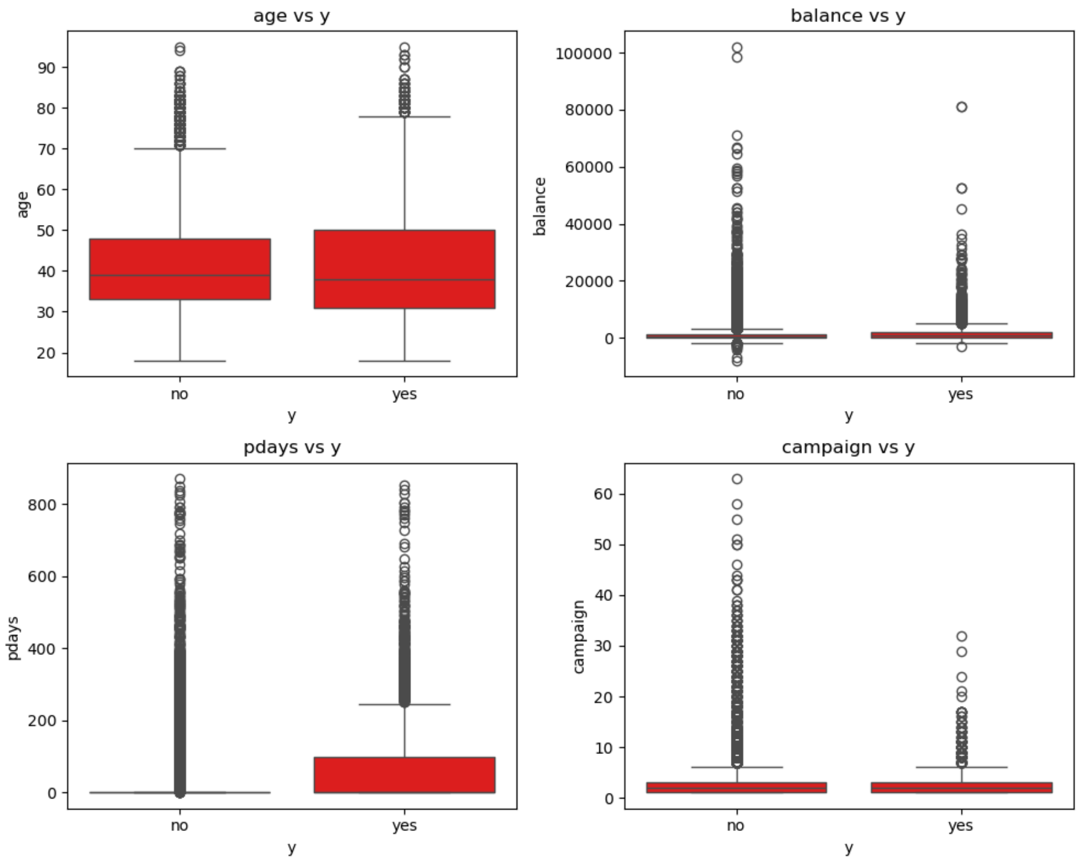
```
Summary Statistics:
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
count	45211.00	45211	45211	45211	45211	45211.00	45211	45211	45211	45211.00	45211	45211.00	45211.00	45211.00	45211.00	45211	45211
unique	NaN	11	3	3	2	NaN	2	2	2	NaN	12	NaN	NaN	NaN	NaN	3	2
top	NaN	blue-collar	married	secondary	no	NaN	yes	no	cellular	NaN	may	NaN	NaN	NaN	NaN	failure	no
freq	NaN	10020	27214	25059	44396	NaN	25130	37967	42305	NaN	13766	NaN	NaN	NaN	NaN	41860	39922
mean	40.94	NaN	NaN	NaN	NaN	1362.27	NaN	NaN	NaN	15.81	NaN	258.16	2.76	40.20	0.58	NaN	NaN
std	10.62	NaN	NaN	NaN	NaN	3044.77	NaN	NaN	NaN	8.32	NaN	257.53	3.10	100.13	2.30	NaN	NaN
min	18.00	NaN	NaN	NaN	NaN	-8019.00	NaN	NaN	NaN	1.00	NaN	0.00	1.00	-1.00	0.00	NaN	NaN
25%	33.00	NaN	NaN	NaN	NaN	72.00	NaN	NaN	NaN	8.00	NaN	103.00	1.00	-1.00	0.00	NaN	NaN
50%	39.00	NaN	NaN	NaN	NaN	448.00	NaN	NaN	NaN	16.00	NaN	180.00	2.00	-1.00	0.00	NaN	NaN
75%	48.00	NaN	NaN	NaN	NaN	1428.00	NaN	NaN	NaN	21.00	NaN	319.00	3.00	-1.00	0.00	NaN	NaN
max	95.00	NaN	NaN	NaN	NaN	102127.00	NaN	NaN	NaN	31.00	NaN	4918.00	63.00	871.00	275.00	NaN	NaN

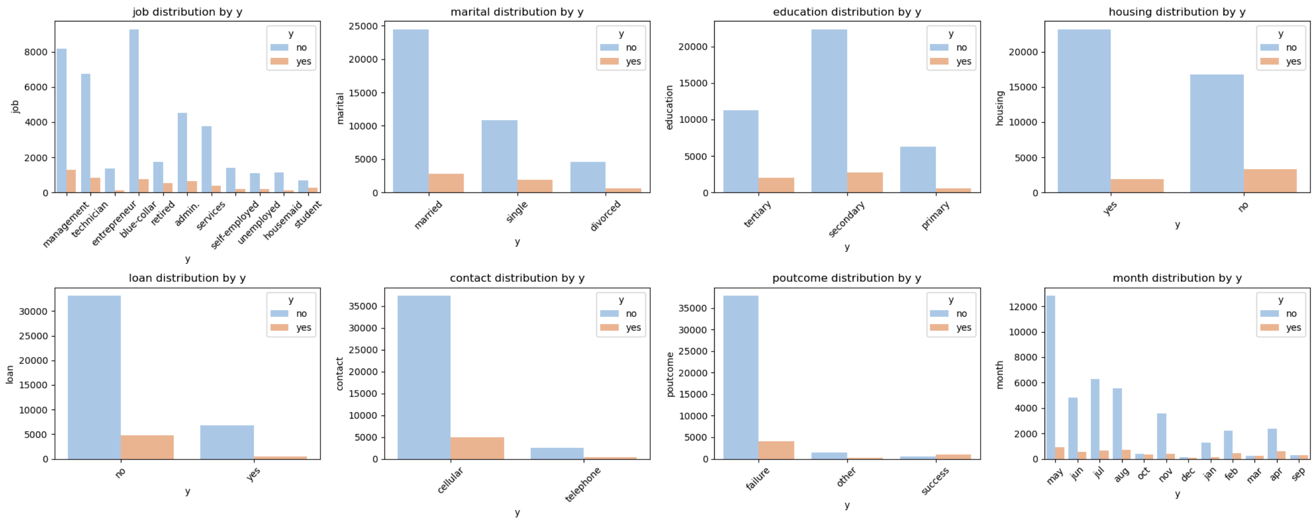
```
==============================
EDA: Distribution of Target Variable (Subscription to Term Deposit)
==============================

Value Counts:
 y
no     39922
yes     5289
Name: count, dtype: int64
Class Proportions:
 y
no     88.3
yes    11.7
Name: proportion, dtype: float64

==============================
EDA: Histogram of Numeric Features
==============================
```




```
==============================
EDA: Boxplots of Numeric Features
==============================
```




```
==============================
EDA: Countplots of Categorical Features
==============================
```



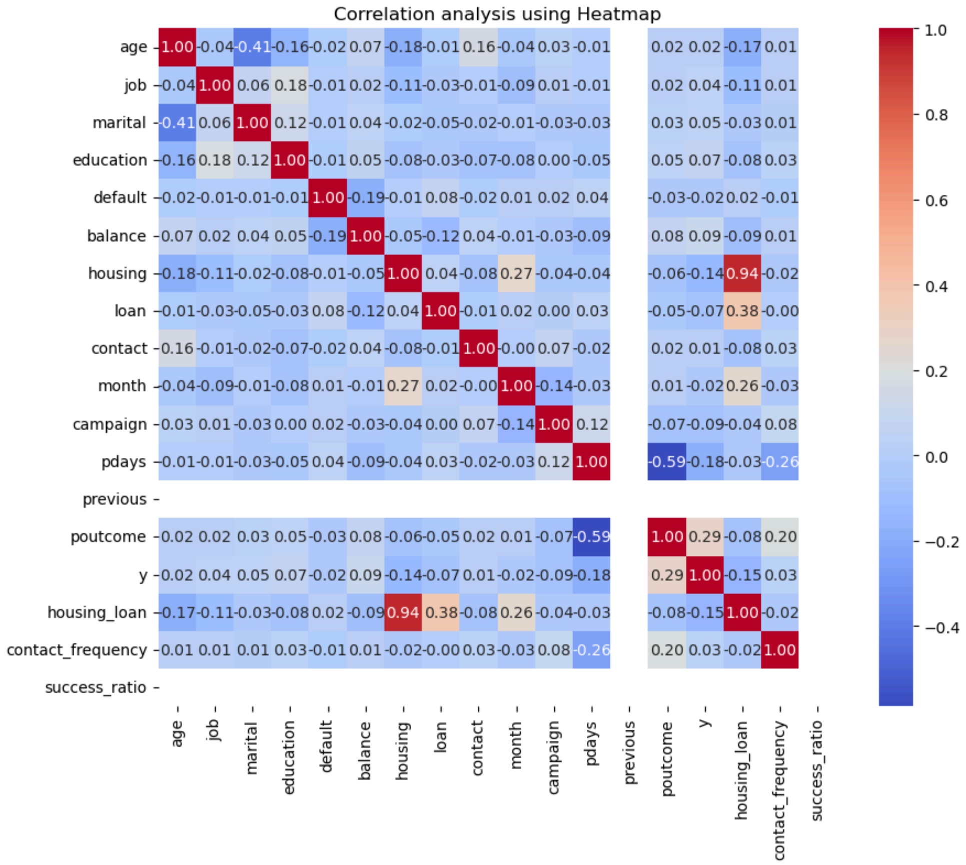
EDA Summary

- The target variable is **highly imbalanced** (~88% no, 12% yes)
- Features like `balance` and `campaign` are **right-skewed**
- `month`, `job`, and `poutcome` show strong relationship with the target variable
- Some features (e.g., `contact`, `education`) have clearly different distributions based on subscription outcome

Feature Engineering & Preprocessing

In [57]:
```
processed_df = bank_dataset_preprocessing(cleaned_df.copy())
correlation_analysis(processed_df)
```

```
Log Transformation Applied to 'campaign' (skewness=1.10)
Log Transformation Applied to 'balance' (skewness=1.07)


Dataset Shape after preprocessing: (45211, 18)
Any Missing Values After Preprocessing..? and have  age                  0
job                 0
marital             0
education           0
default             0
balance             0
housing             0
loan                0
contact             0
month               0
campaign            0
pdays               0
previous            0
poutcome            0
y                   0
housing_loan        0
contact_frequency   0
success_ratio       0
dtype: int64

==============================
Heat Map: Correlation analysis
==============================
```



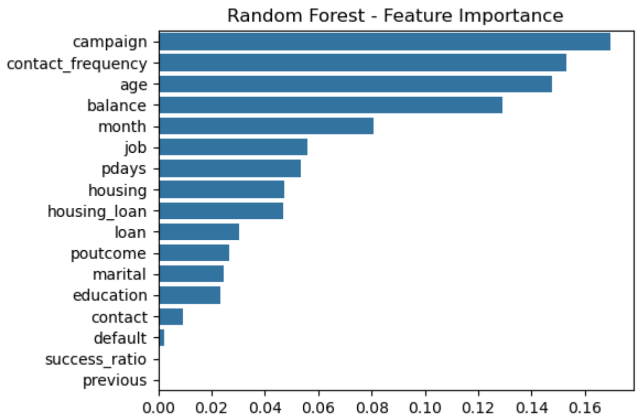
Heatmap Summary

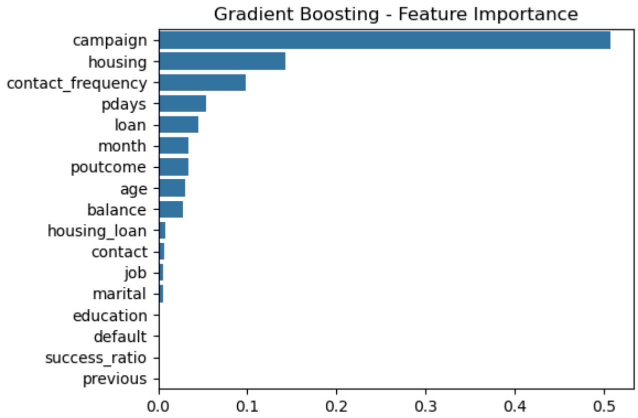
- The target `y` has modest correlation with `poutcome`, `contact_frequency`, and `month`.
- Most features are not strongly correlated with each other, which is good for avoiding multicollinearity.

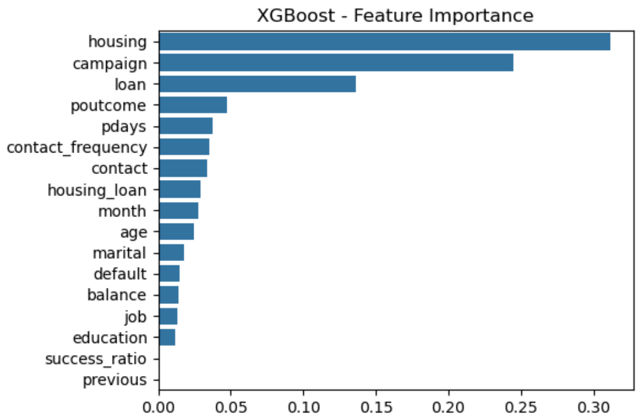
Modeling — Training Baseline Models

In [60]:
```
results = modeling_function(processed_df.copy())
```

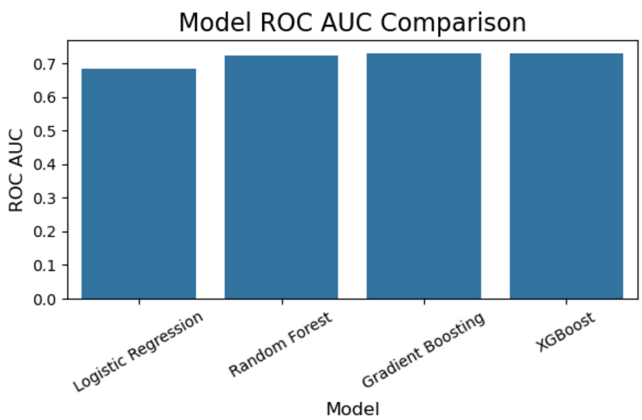
```
Shape of the Features: (45211, 17)
Shape of the Target: (45211,)


Shape of Train dataset: (28934, 17)
Shape of Validation dataset: (7234, 17)
Shape of Test dataset: (9043, 17)

 Distribution of class afte balancing using SMOTE:
y
1    25549
0    25549
Name: count, dtype: int64
```







	Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
0	Logistic Regression	0.699	0.207	0.558	0.302	0.686
1	Random Forest	0.865	0.406	0.326	0.362	0.723
2	Gradient Boosting	0.868	0.428	0.389	0.407	0.729
3	XGBoost	0.876	0.457	0.326	0.381	0.732



Baseline Model Training and Evaluation Summary

- **XGBoost** achieved the highest ROC AUC of **0.732**, closely followed by Gradient Boosting.
- All models show **lower recall** on the minority class, suggesting potential for threshold tuning or further optimization.
- ROC AUC Bar Chart: Highlights superior performance of ensemble models like Random Forest, Gradient Boosting, XGBoost
- Most influential features: `campaign`, `housing`, `contact_frequency`, `loan`, `pdays`

Hyperparameter Tuning & Final Evaluation

In [63]:
```
tuned_results = hypertuning_function(
    results["X_train"], results["y_train"],
    results["X_val"], results["y_val"],
    results["X_test"], results["y_test"]
)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits


Best XGBoost Parameters:
{'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 200, 'subsample': 0.8}
ROC AUC (CV): 0.9570
Fitting 3 folds for each of 36 candidates, totalling 108 fits


Best Gradient Boosting Parameters:
{'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 200, 'subsample': 0.8}
ROC AUC (CV): 0.9592
```

In [64]:
```
hypertuned_model_evaluation(
    {name: result["model"] for name, result in tuned_results.items()},
```

```
    results["X_test"], results["y_test"]
)
```

```
Final Evaluation on Test Set

XGBoost Tuned - Test ROC AUC: 0.7351
              precision    recall  f1-score   support

           0       0.91      0.96      0.93      7985
           1       0.49      0.31      0.38      1058

    accuracy                           0.88      9043
   macro avg       0.70      0.63      0.66      9043
weighted avg       0.86      0.88      0.87      9043


Gradient Boosting Tuned - Test ROC AUC: 0.7329
              precision    recall  f1-score   support

           0       0.91      0.96      0.93      7985
           1       0.47      0.29      0.36      1058

    accuracy                           0.88      9043
   macro avg       0.69      0.62      0.64      9043
weighted avg       0.86      0.88      0.87      9043
```

Final Evaluation on Test Set

I have evaluated the tuned models on the unseen test set. The following are the result

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
XGBoost (Tuned)	0.88	0.49	0.31	0.38	0.735
Gradient Boosting (Tuned)	0.88	0.47	0.29	0.36	0.733

Key Insights

- The **tuned XGBoost model** achieved the best performance with ROC AUC = 0.735 on the test set.
- Both models maintained high overall accuracy (0.88).
- The model performs well on the majority class, but recall on the minority class is still low (~30%).
- Feature importance indicates that `month`, `poutcome`, `campaign`, and `contact_frequency` are strong predictors.
- SMOTE improved recall, but there's still a trade-off between precision and recall.

Summary

This project demonstrates a complete machine learning pipeline for handling real-world class imbalance and tabular data modeling.

- Full EDA, preprocessing, and feature engineering
- Multiple models with tuning
- Final ROC AUC: 0.735 (XGBoost)
- - **XGBoost** is selected as the final model for deployment or reporting due to its stronger test set performance.

---- Next Steps to be achived---

- Improve minority class recall
- Try SHAP/LIME for explainability
- Deploy model

In [ ]: