AAI_510_FinalProject_Team2

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1 MS AAI - 510 - MACHINE LEARNING FUNDAMENTALS

2 Final Project - Diabetes Predictor based on CDC Health Indicators

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This notebook contains our analysis and model for the selected dataset. Source: https://archive.ics.uci.edu/dataset/891/cdc+diabetes+health+indicatorsA

2.1.1 Data understanding

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
ID	ID	Integer		Patient ID		no
Diabetes_binary	Target	Binary		0 = no diabetes 1 = prediabetes or diabetes		no
HighBP	Feature	Binary		0 = no high BP 1 = high BP		no
HighChol	Feature	Binary		0 = no high cholesterol 1 = high cholesterol		no
CholCheck	Feature	Binary		0 = no cholesterol check in 5 years 1 = yes cholesterol check in 5 years		no
BMI	Feature	Integer		Body Mass Index		no
Smoker	Feature	Binary		Have you smoked at least 100 cigarettes in your entire life? [Note: 5 packs = 100 cigarettes] 0 = no 1 = yes		no
Stroke	Feature	Binary		(Ever told) you had a stroke. 0 = no 1 = yes		no
HeartDiseaseorAttack	Feature	Binary		Coronary heart disease (CHD) or myocardial infarction (MI) 0 = no 1 = yes		no
PhysActivity	Feature	Binary		Physical activity in past 30 days - not including job 0 = no 1 = yes		no
Fruits	Feature	Binary		Consume fruit 1 or more times per day 0 = no 1 = yes		no
Veggies	Feature	Binary		Consume vegetables 1 or more times per day 0 = no 1 = yes		no
HvyAlcoholConsump	Feature	Binary		Heavy drinkers (adult men >14 drinks/week, women >7 drinks/week) 0 = no 1 = yes		no
AnyHealthcare	Feature	Binary		Any kind of health care coverage (insurance, HMO, etc.) 0 = no 1 = yes		no

Variable Name	Role	Type	Demographics	Description	Units	Missing Values
NoDocbcCost	Feature	Binary		In past 12 months, needed to see doctor but could not because of cost? 0 = no 1 = yes		no
GenHlth	Feature	Integer		General health (1 = excellent, 2 = very good, 3 = good, 4 = fair, 5 = poor)		no
MentHlth	Feature	Integer		Days mental health not good in past 30 days (1-30)		no
PhysHlth	Feature	Integer		Days physical health not good in past 30 days (1-30)		no
DiffWalk	Feature	Binary		Serious difficulty walking or climbing stairs? 0 = no 1 = yes		no
Sex	Feature	Binary	Sex	0 = female 1 = male		no
Age	Feature	Integer	Age	13-level age category (_AGEG5YR see codebook): 1 = 18-24, 9 = 60-64, 13 = 80+		no
Education	Feature	Integer	Education Level	Education level (EDUCA see codebook): 1 = Never attended/Kindergarten, 2 = Grades 1-8, 3 = Grades 9-11, 4 = HS/GED, 5 = College 1-3 yrs, 6 = College grad		no
Income	Feature	Integer	Income	Income scale (INCOME2 see codebook): 1 = <$10k, 5 = <$35k, 8 = $75k+		no

Note:
_AGEG5YR is a calculated variable for a fourteen-level age category, derived from AGE.

Value	Age Group	Description
1	Age 18 to 24	Respondents with age between 18 and 24 years (18 AGE 24)
2	Age 25 to 29	Respondents with age between 25 and 29 years (25 AGE 29)
3	Age 30 to 34	Respondents with age between 30 and 34 years (30 AGE 34)
4	Age 35 to 39	Respondents with age between 35 and 39 years (35 AGE 39)
5	Age 40 to 44	Respondents with age between 40 and 44 years (40 AGE 44)
6	Age 45 to 49	Respondents with age between 45 and 49 years (45 AGE 49)
7	Age 50 to 54	Respondents with age between 50 and 54 years (50 AGE 54)
8	Age 55 to 59	Respondents with age between 55 and 59 years (55 AGE 59)
9	Age 60 to 64	Respondents with age between 60 and 64 years (60 AGE 64)
10	Age 65 to 69	Respondents with age between 65 and 69 years (65 AGE 69)
11	Age 70 to 74	Respondents with age between 70 and 74 years (70 AGE 74)
12	Age 75 to 79	Respondents with age between 75 and 79 years (75 AGE 79)
13	Age 80 or older	Respondents with age between 80 and 99 years (80 AGE 99)
14	Don't know/Refused/Missing	Respondents who didn't know, were not sure, or refused to report

2.2 Problem statement and justification for the proposed approach.

According to the CDC, 11.6% of the population in the United States from all age groups had diabetes in 2021. That's 38.4 million Americans from which 39.7 million were diagnosed and an estimated 8.7 million are unaware they have the deadly condition. About 1.2 million Americans get diagnosed with diabetes every year. Diabetes is expensive, underdiagnosed, and when caught too late, often irreversible.

The solution isn't more doctors or more clinics, it's smarter systems, systems that can detect risk before complications arise. That's where our model fits in. We have built a machine learning pipeline powered by CDC health indicators, cloud native API first and fully compatible with modern EHR environments.

2.2.1 Imports

[6]:
```
# Standard libraries
import os
import warnings
import joblib

# Data handling
import numpy as np
import pandas as pd

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
import shap

# Data source
from ucimlrepo import fetch_ucirepo

# Scikit-learn: Preprocessing and Model Selection
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler

# Scikit-learn: Models
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.linear_model import LogisticRegression

# XGBoost
from xgboost import XGBClassifier as XGBoostClassifier

# Scikit-learn: Metrics and Evaluation
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, ConfusionMatrixDisplay,
    roc_auc_score, average_precision_score,
    roc_curve, auc, RocCurveDisplay,
    precision_recall_curve, make_scorer
)

# Scikit-learn: Warnings
```

```
from sklearn.exceptions import ConvergenceWarning

# Sampling
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
from IPython.display import display
```

2.2.2 Config & Warnings

[7]:
```
warnings.filterwarnings("ignore", category=ConvergenceWarning)
warnings.filterwarnings("ignore", category=FutureWarning, message="The SAMME.R␣
↪algorithm.*")
sns.set_theme()
shap.initjs()
RANDOM_SEED = 42
```

```
<IPython.core.display.HTML object>
```

Instead of writing everything in one long script, we broke down into separate reusable functions for each step like data loading, pre-processing, EDA model training, evaluation, and plotting.

2.2.3 Data Loading & Preprocessing

After bringing in the CDC diabetes dataset, one of the first things we did was visualize the distribution of our target variable, Diabetes_binary, with a simple bar plot. This chart basically counts up how many people in our data do or do not have diabetes. Right away, you'll notice a huge imbalance: the vast majority of individuals are not diabetic, and only a smaller fraction are.

[8]:
```
def load_and_prepare_data():
    cdc_diabetes_health_indicators = fetch_ucirepo(id=891)
    df = cdc_diabetes_health_indicators.data.original.dropna()
    X = cdc_diabetes_health_indicators.data.features.loc[df.index]
    y = cdc_diabetes_health_indicators.data.targets.loc[df.index]
    return df, X, y

def data_count(df):
    df['Diabetes_binary'].value_counts().sort_index().plot(kind='bar', title =␣
↪'Diabetes')
    plt.xticks(rotation = 0)
    plt.ylabel('Frequency')
    plt.tight_layout()
    plt.show()
    print(f"Data count: {df['Diabetes_binary'].value_counts()}")

def split_data(X, y, test_size=0.2, random_state=RANDOM_SEED):
    return train_test_split(X, y, test_size=test_size,␣
↪random_state=random_state)
```

```
def select_features(X, columns):
    return X[columns]
```

2.2.4 Run EDA

Moving into exploratory data analysis, we used a correlation heatmap, which is basically a colored grid that shows how every feature in our dataset relates to every other feature—including our target. Each square in the grid tells us whether two features move together or not. For example, a strong positive value between "HighBP" and "Diabetes_binary" means people with high blood pressure are more likely to be diabetic. Meanwhile, values close to zero mean there's little to no connection. This heatmap is a great tool for spotting which features might help our predictions and for warning us if some features are too similar and could cause problems in modeling.

[9]:
```
def run_eda(df):
    print("\n===== Data Head =====")
    print(df.head())
    print("\n===== Data Description =====")
    print(df.describe())
    print("\n===== Data Info =====")
    print(df.info())
    # print("\n===== Value Counts for Each Column =====")
    # for col in df.columns:
    #     print(f"\n{col} value counts:")
    #     print(df[col].value_counts())
    # Correlation heatmap
    plt.figure(figsize=(14, 8))
    sns.heatmap(df.drop(columns=['ID'], errors='ignore').corr(), cmap='BrBG',␣
↪linewidths=2, annot=True, fmt=".1f")
    plt.title('Correlation Heatmap')
    plt.show()
    # Bar chart: feature correlation with target
    if 'Diabetes_binary' in df.columns:
        corr_matrix = df.drop(columns=['ID'], errors='ignore').corr()
        target_corr = corr_matrix['Diabetes_binary'].drop('Diabetes_binary')
        plt.figure(figsize=(10, 5))
        target_corr.sort_values(ascending=False).plot(kind='bar', color='teal')
        plt.title('Feature Correlation with Diabetes_binary')
        plt.ylabel('Correlation Coefficient')
        plt.xlabel('Feature')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()
    # Feature distributions
    features = df.drop(columns=['Diabetes_binary', 'ID'], errors='ignore')
    plt.figure(figsize=(20, 16))
    for i, col in enumerate(features.columns):
        plt.subplot(6, 4, i + 1)
```

```
        sns.histplot(features[col])
        plt.xlabel(col)
        plt.ylabel('count')
        plt.grid()
        plt.tight_layout()
    plt.show()
```

2.2.5 Resampling Utilities

[10]:
```
def resample_data(X, y, method=None):
    if method == 'under':
        sampler = RandomUnderSampler(random_state=RANDOM_SEED)
        X_res, y_res = sampler.fit_resample(X, y)
        return X_res, y_res
    elif method == 'smote':
        sampler = SMOTE(random_state=RANDOM_SEED)
        X_res, y_res = sampler.fit_resample(X, y)
        return X_res, y_res
    else:
        return X, y
```

2.2.6 Model Training & Evaluation

We compared several different scenarios to understand how data balance and hyperparameter tuning affect our results. Here's what we did: Original Data with Tuning: We trained each model—Logistic Regression, Random Forest, XGBoost, and Gradient Boosting—on the original, imbalanced data, using grid search to tune their parameters. Undersampling: Since our data has way more non-diabetic cases than diabetic, we used random undersampling to reduce the size of the majority class, making the classes balanced. Then we trained and tuned the same models. SMOTE (Synthetic Minority Oversampling Technique): Here, we used a technique to increase the minority class by generating synthetic diabetic samples, again training and tuning our models. Models Without Tuning: We also wanted to see how much tuning matters, so we trained all four models again—on all three data versions—using their default hyperparameters.

After training our models, we use confusion matrices to really see how each one is performing. Each confusion matrix is a simple 2x2 table that tells us not just how many predictions were right, but what kind of mistakes the model made. The top left cell counts the people correctly identified as not diabetic, and the bottom right shows the correctly identified diabetics. The off-diagonal cells tell us about false alarms and, more importantly, the missed real cases—which is a big concern in healthcare. By comparing these grids across different models, we get a much clearer picture than we'd get from accuracy alone.

The ROC curve is a classic way to see how well our models distinguish between diabetic and non-diabetic cases at various thresholds. It plots the true positive rate against the false positive rate, and the closer the curve hugs the top-left corner, the better the model is. If the curve follows the diagonal, it's basically guessing. We also get an AUC score, which tells us, in one number, how good the model is overall—where 1 is perfect and 0.5 is random. For our best models, an AUC around 0.83 is really strong, especially given the difficulty of the task.

Because diabetes cases are rare in the data, the precision-recall curve is another super important graph. Here, we're balancing two things: how many real cases we're catching (recall), and how many of the cases we label as diabetic are actually correct (precision). When the data is imbalanced, this curve gives a much more honest look at performance than ROC curves alone. A high area under this curve means our model isn't just accurate overall, but it's actually catching diabetics without too many false alarms—a crucial tradeoff in real-world healthcare. A value of 0.43 on the precision-recall curve means that, on average, 43% of the positive predictions made by our model are actually correct, when balancing both precision and recall across all possible thresholds.

[11]:
```
def get_models():
    return {
        'Logistic Regression': LogisticRegression(random_state=RANDOM_SEED,␣
 ↪max_iter=1000),
        'Random Forest': RandomForestClassifier(random_state=RANDOM_SEED),
        'XG Boost Classifier': XGBoostClassifier(random_state=RANDOM_SEED,␣
 ↪eval_metric='logloss'),
        'Gradient Boosting Classifier':␣
 ↪GradientBoostingClassifier(random_state=RANDOM_SEED),
    }

def get_param_grids():
    return {
        'Logistic Regression': {
            'C': [0.1, 1, 10, 100],
            'solver': ['liblinear', 'lbfgs'],
            'class_weight': ['balanced', {0: 1, 1: 2}, {0: 1, 1: 3}]
        },
        'Random Forest': {
            'n_estimators': [100, 200, 300],
            'max_depth': [10, 20, None],
            'min_samples_split': [2, 5, 10],
            'class_weight': ['balanced', 'balanced_subsample']
        },
        'XG Boost Classifier': {
            'n_estimators': [100, 200, 300],
            'max_depth': [3, 6, 10],
            'learning_rate': [0.01, 0.1, 0.2],
            'subsample': [0.8, 1.0],
            'scale_pos_weight': [1, 2, 3]
        },
        'Gradient Boosting Classifier': {
            'n_estimators': [100, 200],
            'max_depth': [3, 5, 7],
            'learning_rate': [0.01, 0.1, 0.2],
            'subsample': [0.8, 1.0]
        }
    }
```

```python
def tune_model(model, param_grid, X_train, y_train):
    scorer = make_scorer(roc_auc_score)
    grid_search = GridSearchCV(
        model,
        param_grid,
        cv=3,
        scoring=scorer,
        n_jobs=-1,
        verbose=1
    )
    grid_search.fit(X_train, y_train.squeeze())
    print(f"Best parameters: {grid_search.best_params_}")
    print(f"Best CV score: {grid_search.best_score_:.4f}")
    return grid_search.best_estimator_

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted',␣
 ↪zero_division=0)
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    cm = confusion_matrix(y_test, y_pred)
    return accuracy, precision, recall, f1, cm, y_pred

def save_model(model, name, save_dir='../models'):
    os.makedirs(save_dir, exist_ok=True)
    filename = os.path.join(save_dir, f"{name.replace(' ', '_')}_model.pkl")
    joblib.dump(model, filename)
    print(f"Saved {name} to {filename}")

def plot_shap_feature_importance(model, X, max_display=11, title="SHAP Feature␣
 ↪Importance (Bar Chart)"):
    # Ensure X is a DataFrame and columns match model training
    feature_names = list(X.columns)
    X_array = X.values

    # Use TreeExplainer for tree-based models
    if hasattr(model, "feature_importances_"):
        explainer = shap.TreeExplainer(model)
        shap_values = explainer.shap_values(X_array)
        # For tree models, shap_values is (n_samples, n_features)
        shap.summary_plot(shap_values, X, feature_names=feature_names,␣
 ↪plot_type="bar", max_display=max_display, show=False)
    else:
        explainer = shap.Explainer(model, X)
```

```
        shap_values = explainer(X)
        shap.plots.bar(shap_values, max_display=max_display, show=False)
    plt.title(title)
    plt.show()


def plot_all_confusion_matrices(trained_models, X_test, y_test):
    n = len(trained_models)
    cols = 2
    rows = (n + cols - 1) // cols
    fig, axes = plt.subplots(rows, cols, figsize=(6 * cols, 5 * rows))
    axes = axes.flatten()
    for i, (model_name, model) in enumerate(trained_models.items()):
        y_pred = model.predict(X_test)
        cm = confusion_matrix(y_test, y_pred)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=model.
 ↪classes_)
        disp.plot(ax=axes[i], cmap='Blues', colorbar=False)
        axes[i].set_title(f"{model_name} (Acc: {accuracy_score(y_test, y_pred):.
 ↪2f})")
    for j in range(i + 1, len(axes)):
        fig.delaxes(axes[j])
    plt.tight_layout()
    plt.show()

def plot_all_roc_pr_curves(trained_models, X_test, y_test):
    plt.figure(figsize=(12, 10))
    for model_name, model in trained_models.items():
        if hasattr(model, "predict_proba"):
            y_score = model.predict_proba(X_test)[:, 1]
        else:
            y_score = model.decision_function(X_test)
        # ROC Curve
        fpr, tpr, _ = roc_curve(y_test, y_score)
        roc_auc = auc(fpr, tpr)
        plt.subplot(2, 1, 1)
        plt.plot(fpr, tpr, lw=2, label=f'{model_name} (AUC = {roc_auc:.2f})')
        # PR Curve
        precision, recall, _ = precision_recall_curve(y_test, y_score)
        avg_precision = average_precision_score(y_test, y_score)
        plt.subplot(2, 1, 2)
        plt.plot(recall, precision, lw=2, label=f'{model_name} (AP =␣
 ↪{avg_precision:.2f})')
    plt.subplot(2, 1, 1)
    plt.title('ROC Curve')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

```
    plt.legend(loc='lower right')
    plt.subplot(2, 1, 2)
    plt.title('Precision-Recall Curve')
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.legend(loc='lower left')
    plt.tight_layout()
    plt.show()
```

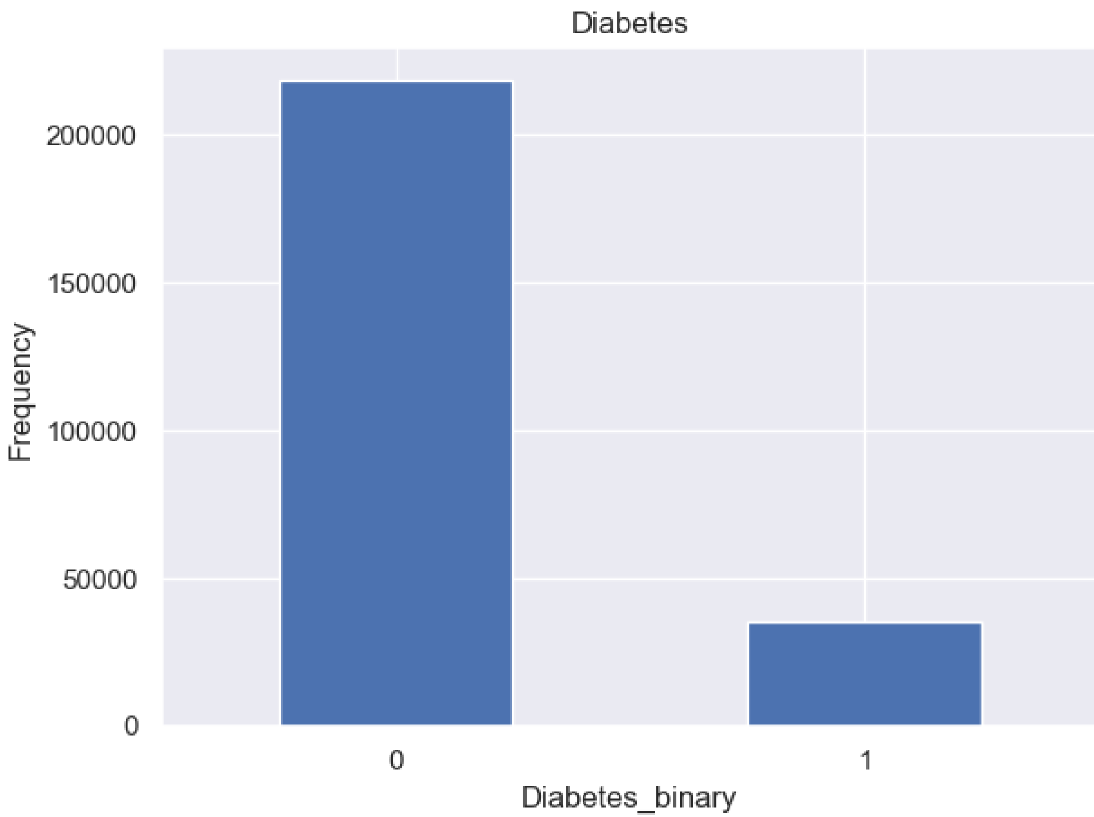
2.2.7 Main Experiment Pipeline

[12]:
```
def model_training_with_tuning(X_train, y_train, X_test, y_test,␣
 ↪resample_method=None, axes_cmap='Greens'):
    models = get_models()
    param_grids = get_param_grids()
    X_res, y_res = resample_data(X_train, y_train, method=resample_method)
    results = []
    trained_models = {}
    num_models = len(models)
    cols = 2
    rows = (num_models + cols - 1) // cols
    for i, (model_name, model) in enumerate(models.items()):
        print(f"\nTraining {model_name} ({'resampled' if resample_method else␣
 ↪'original'})...")
        tuned_model = tune_model(model, param_grids[model_name], X_res, y_res)
        trained_models[model_name] = tuned_model
        acc, prec, rec, f1, cm, y_pred = evaluate_model(tuned_model, X_test,␣
 ↪y_test)
        if hasattr(tuned_model, "predict_proba"):
            y_score = tuned_model.predict_proba(X_test)[:, 1]
        else:
            y_score = tuned_model.decision_function(X_test)
        roc_auc = roc_auc_score(y_test, y_score)
        avg_precision = average_precision_score(y_test, y_score)
        results.append([model_name, acc, prec, rec, f1, roc_auc, avg_precision])
        save_model_name = model_name.replace(' ', '_') + ('_resampled_' +␣
 ↪resample_method if resample_method else '_original')
        save_model(tuned_model, save_model_name)
    results_df = pd.DataFrame(results, columns=['Model', 'Test Accuracy',␣
 ↪'Precision', 'Recall', 'F1-Score', 'ROC-AUC', 'Avg Precision'])
    print(results_df.sort_values(by='Test Accuracy', ascending=False))
    # All confusion matrices in a grid
    plot_all_confusion_matrices(trained_models, X_test, y_test)
    # All ROC and PR curves in a grid
    plot_all_roc_pr_curves(trained_models, X_test, y_test)
    # SHAP plots
    # for model_name, model in trained_models.items():
```

```python
    #     print(f"SHAP Feature Importance for {model_name}:")
    #     plot_shap_feature_importance(model, X_test, title=f"SHAP Feature␣
↪Importance: {model_name}")
    return results_df, trained_models

def model_training_with_no_tuning(X_train, y_train, X_test, y_test,␣
↪resample_method=None, axes_cmap='Oranges'):
    models = get_models()
    X_res, y_res = resample_data(X_train, y_train, method=resample_method)
    results = []
    trained_models = {}
    num_models = len(models)
    cols = 2
    rows = (num_models + cols - 1) // cols
    for i, (model_name, model) in enumerate(models.items()):
        print(f"\nTraining {model_name} (no tuning, {'resampled' if␣
↪resample_method else 'original'})...")
        model.fit(X_res, y_res.squeeze())
        acc, prec, rec, f1, cm, y_pred = evaluate_model(model, X_test, y_test)
        if hasattr(model, "predict_proba"):
            y_score = model.predict_proba(X_test)[:, 1]
        else:
            y_score = model.decision_function(X_test)
        roc_auc = roc_auc_score(y_test, y_score)
        avg_precision = average_precision_score(y_test, y_score)
        results.append([model_name, acc, prec, rec, f1, roc_auc, avg_precision])
        trained_models[model_name] = model
        save_model_name = model_name.replace(' ', '_') + '_no_tuning' +␣
↪('_resampled_' + resample_method if resample_method else '_original')
        save_model(model, save_model_name)
    results_df = pd.DataFrame(results, columns=['Model', 'Test Accuracy',␣
↪'Precision', 'Recall', 'F1-Score', 'ROC-AUC', 'Avg Precision'])
    print(results_df.sort_values(by='Test Accuracy', ascending=False))
    # All confusion matrices in a grid
    plot_all_confusion_matrices(trained_models, X_test, y_test)
    # All ROC and PR curves in a grid
    plot_all_roc_pr_curves(trained_models, X_test, y_test)
    # SHAP plots
    # for model_name, model in trained_models.items():
    #     print(f"SHAP Feature Importance for {model_name} (no tuning):")
    #     plot_shap_feature_importance(model, X_test, title=f"SHAP Feature␣
↪Importance: {model_name} (no tuning)")
    return results_df, trained_models
```

2.2.8 Main

[13]:
```
df, X, y = load_and_prepare_data()
data_count(df)
selected_columns = [
    'GenHlth','HighBP','Age','BMI','HighChol','Sex','Income',
    'HvyAlcoholConsump','CholCheck','PhysHlth','HeartDiseaseorAttack'
]
run_eda(df)
```

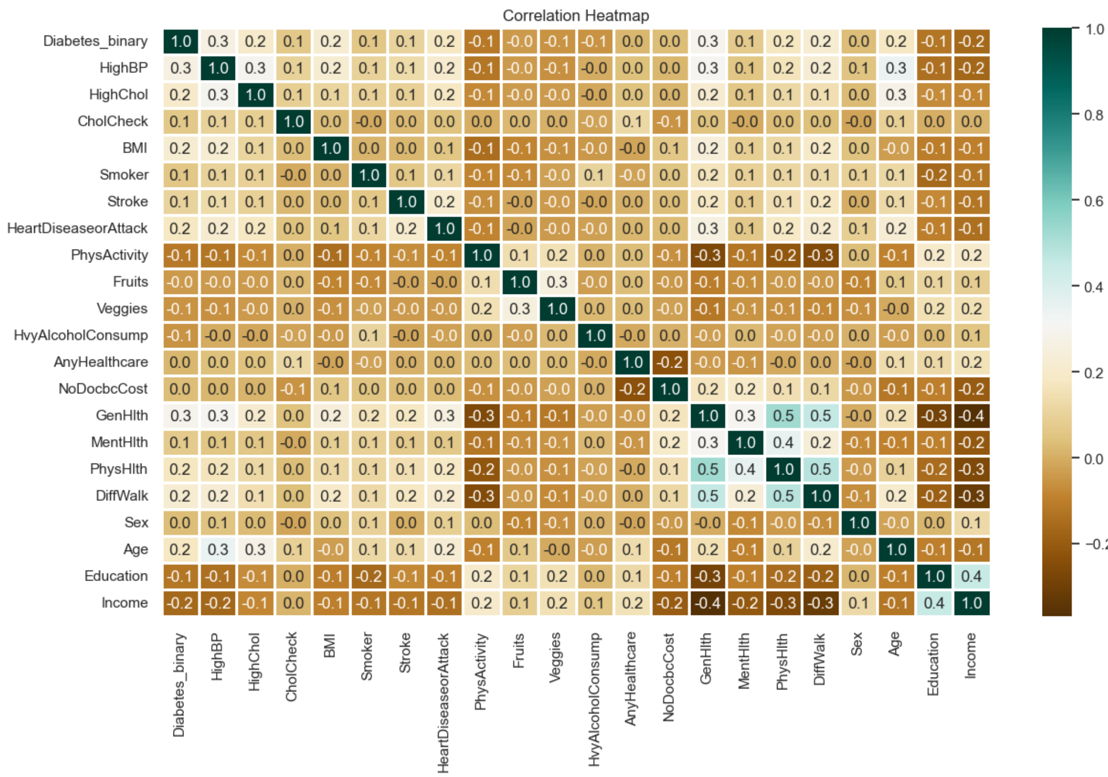


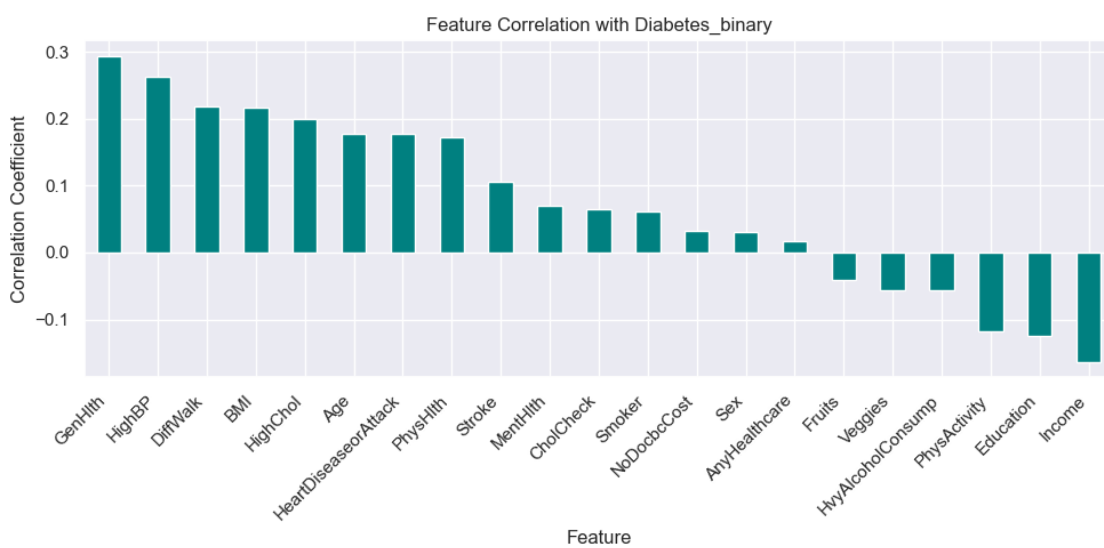

```
Data count: Diabetes_binary
0    218334
1     35346
Name: count, dtype: int64

===== Data Head =====
   ID  Diabetes_binary  HighBP  HighChol  CholCheck  BMI  Smoker  Stroke  \
0   0                0       1         1          1   40       1       0
1   1                0       0         0          0   25       1       0
2   2                0       1         1          1   28       0       0
3   3                0       1         0          1   27       0       0
4   4                0       1         1          1   24       0       0
```

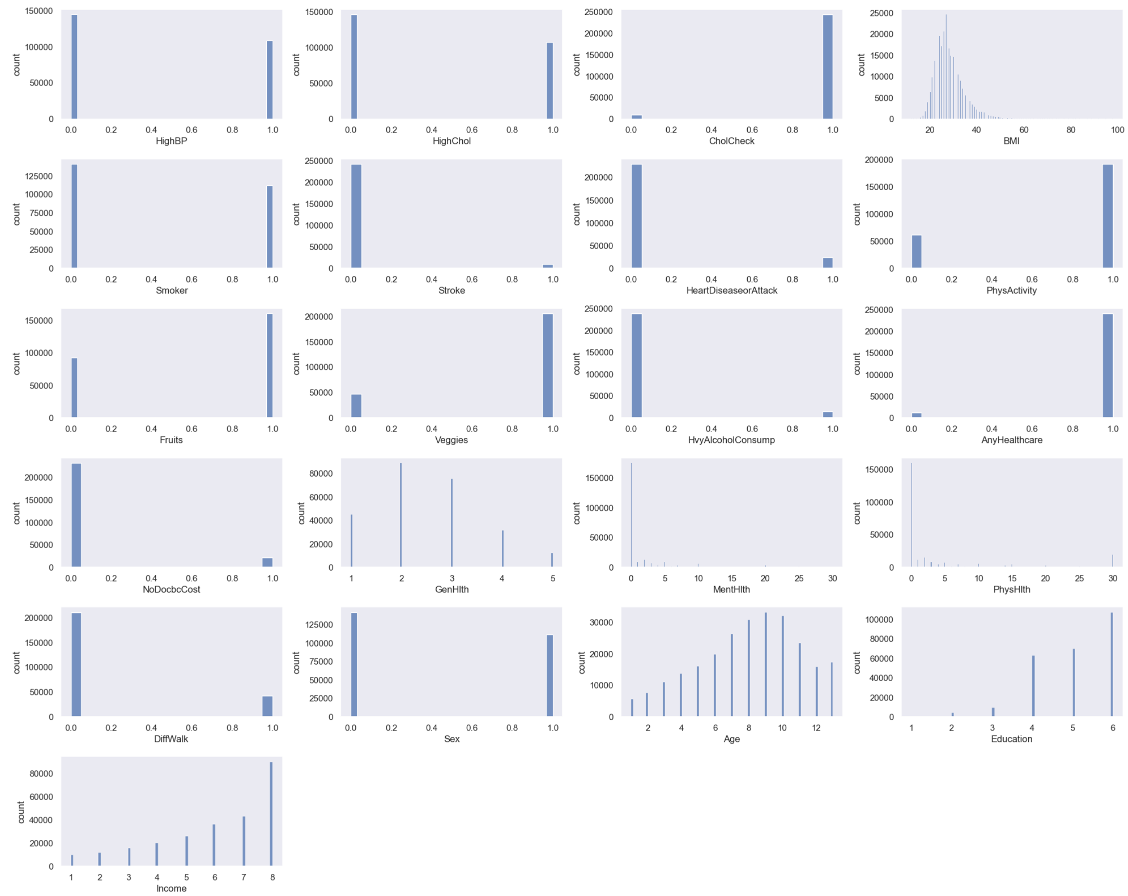
```
   HeartDiseaseorAttack  PhysActivity  …  AnyHealthcare  NoDocbcCost  \
0                     0             0  …              1            0
1                     0             1  …              0            1
2                     0             0  …              1            1
3                     0             1  …              1            0
4                     0             1  …              1            0

   GenHlth  MentHlth  PhysHlth  DiffWalk  Sex  Age  Education  Income
0        5        18        15         1    0    9          4       3
1        3         0         0         0    0    7          6       1
2        5        30        30         1    0    9          4       8
3        2         0         0         0    0   11          3       6
4        2         3         0         0    0   11          5       4

[5 rows x 23 columns]

===== Data Description =====
                  ID  Diabetes_binary         HighBP       HighChol  \
count  253680.000000    253680.000000  253680.000000  253680.000000
mean   126839.500000         0.139333       0.429001       0.424121
std     73231.252481         0.346294       0.494934       0.494210
min         0.000000         0.000000       0.000000       0.000000
25%     63419.750000         0.000000       0.000000       0.000000
50%    126839.500000         0.000000       0.000000       0.000000
75%    190259.250000         0.000000       1.000000       1.000000
max    253679.000000         1.000000       1.000000       1.000000

           CholCheck            BMI         Smoker         Stroke  \
count  253680.000000  253680.000000  253680.000000  253680.000000
mean        0.962670      28.382364       0.443169       0.040571
std         0.189571       6.608694       0.496761       0.197294
min         0.000000      12.000000       0.000000       0.000000
25%         1.000000      24.000000       0.000000       0.000000
50%         1.000000      27.000000       0.000000       0.000000
75%         1.000000      31.000000       1.000000       0.000000
max         1.000000      98.000000       1.000000       1.000000

       HeartDiseaseorAttack   PhysActivity  …  AnyHealthcare    NoDocbcCost  \
count         253680.000000  253680.000000  …  253680.000000  253680.000000
mean               0.094186       0.756544  …       0.951053       0.084177
std                0.292087       0.429169  …       0.215759       0.277654
min                0.000000       0.000000  …       0.000000       0.000000
25%                0.000000       1.000000  …       1.000000       0.000000
50%                0.000000       1.000000  …       1.000000       0.000000
75%                0.000000       1.000000  …       1.000000       0.000000
max                1.000000       1.000000  …       1.000000       1.000000
```

```
            GenHlth       MentHlth       PhysHlth       DiffWalk  \
count  253680.000000  253680.000000  253680.000000  253680.000000
mean        2.511392       3.184772       4.242081       0.168224
std         1.068477       7.412847       8.717951       0.374066
min         1.000000       0.000000       0.000000       0.000000
25%         2.000000       0.000000       0.000000       0.000000
50%         2.000000       0.000000       0.000000       0.000000
75%         3.000000       2.000000       3.000000       0.000000
max         5.000000      30.000000      30.000000       1.000000

                Sex            Age      Education         Income
count  253680.000000  253680.000000  253680.000000  253680.000000
mean        0.440342       8.032119       5.050434       6.053875
std         0.496429       3.054220       0.985774       2.071148
min         0.000000       1.000000       1.000000       1.000000
25%         0.000000       6.000000       4.000000       5.000000
50%         0.000000       8.000000       5.000000       7.000000
75%         1.000000      10.000000       6.000000       8.000000
max         1.000000      13.000000       6.000000       8.000000

[8 rows x 23 columns]

===== Data Info =====
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253680 entries, 0 to 253679
Data columns (total 23 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   ID                    253680 non-null  int64
 1   Diabetes_binary       253680 non-null  int64
 2   HighBP                253680 non-null  int64
 3   HighChol              253680 non-null  int64
 4   CholCheck             253680 non-null  int64
 5   BMI                   253680 non-null  int64
 6   Smoker                253680 non-null  int64
 7   Stroke                253680 non-null  int64
 8   HeartDiseaseorAttack  253680 non-null  int64
 9   PhysActivity          253680 non-null  int64
 10  Fruits                253680 non-null  int64
 11  Veggies               253680 non-null  int64
 12  HvyAlcoholConsump     253680 non-null  int64
 13  AnyHealthcare         253680 non-null  int64
 14  NoDocbcCost           253680 non-null  int64
 15  GenHlth               253680 non-null  int64
 16  MentHlth              253680 non-null  int64
 17  PhysHlth              253680 non-null  int64
 18  DiffWalk              253680 non-null  int64
 19  Sex                   253680 non-null  int64
```

```
 20  Age                     253680 non-null  int64
 21  Education               253680 non-null  int64
 22  Income                  253680 non-null  int64
dtypes: int64(23)
memory usage: 44.5 MB
None
```







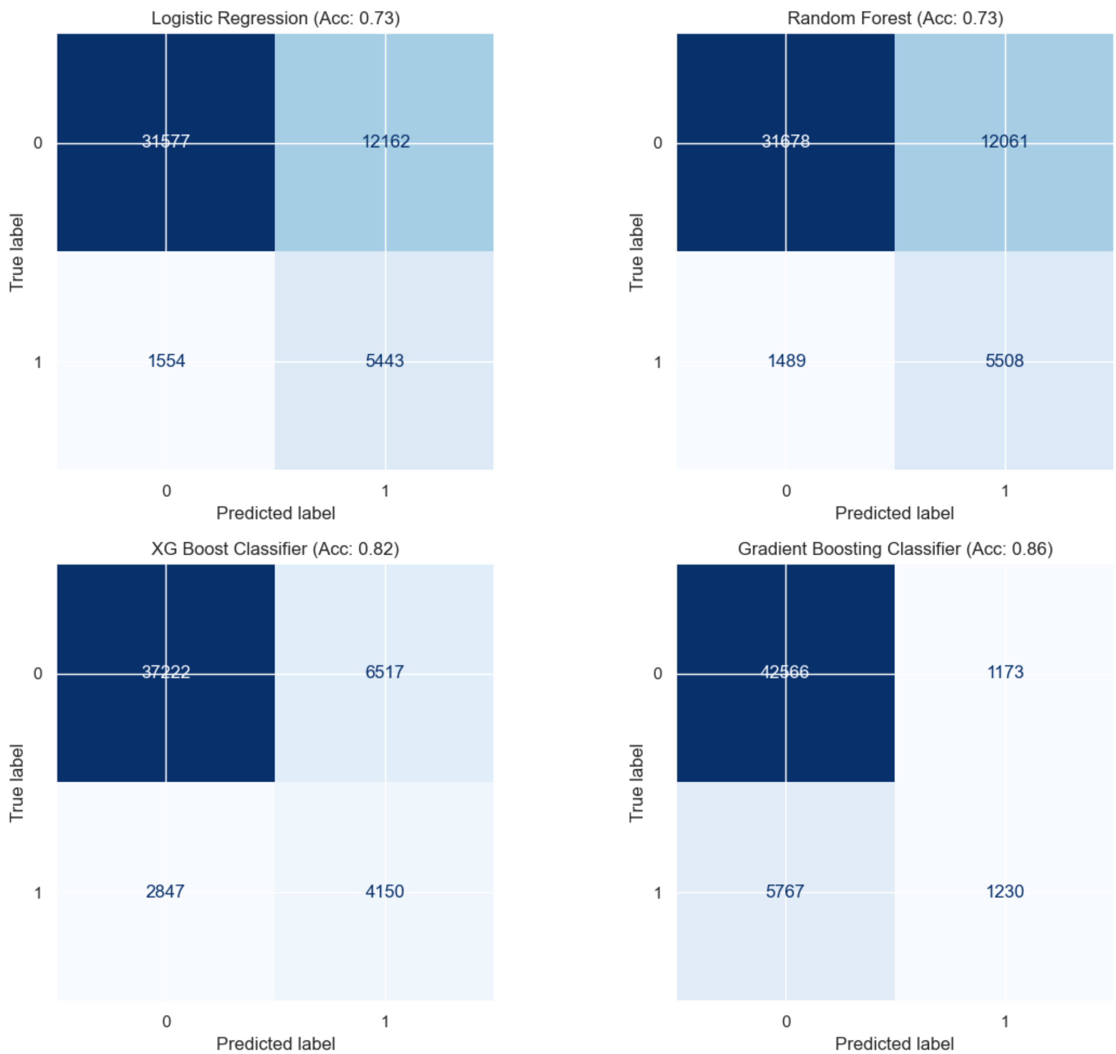
[14]:
```
all_results = []
```

2.2.9 Train model on original (unbalanced) data

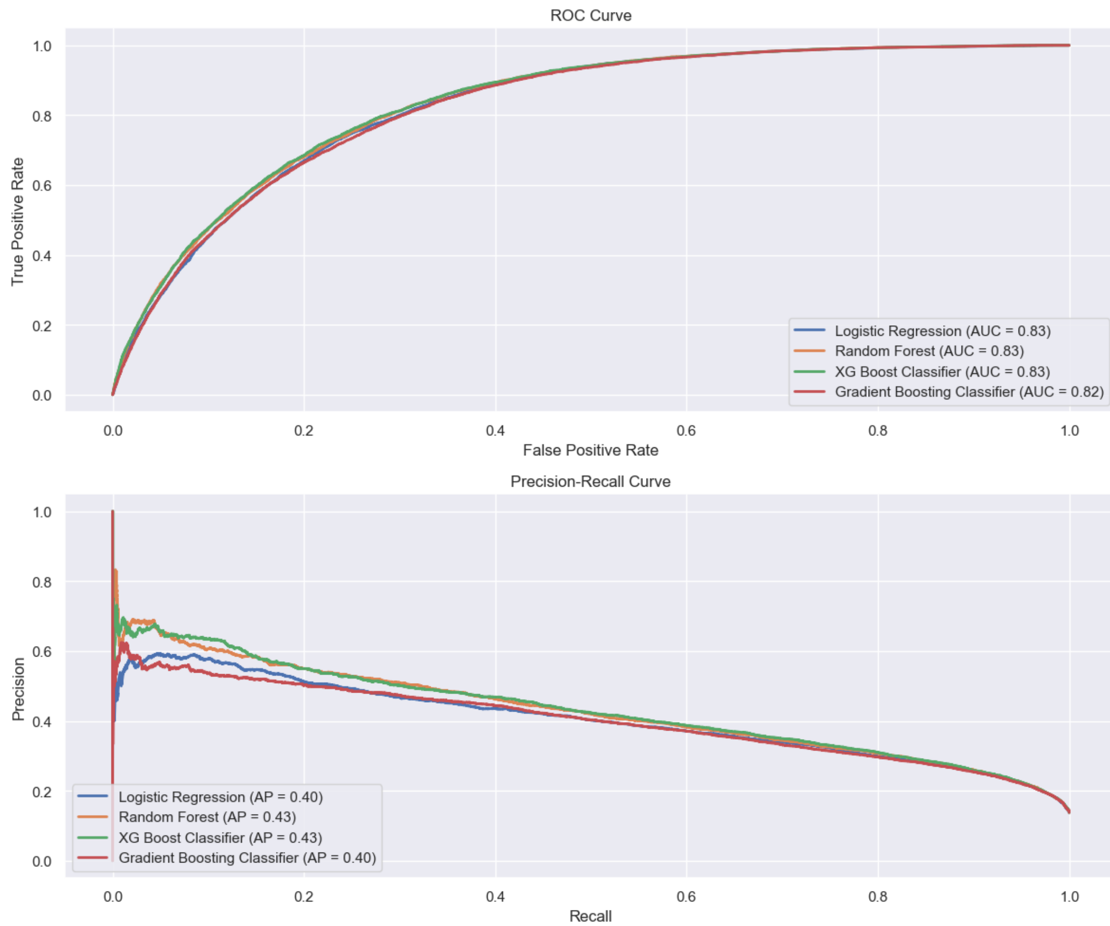
[15]:
```
X_train, X_test, y_train, y_test = split_data(X[selected_columns], y)
res_df, _ = model_training_with_tuning(X_train, y_train, X_test, y_test,
 ↪resample_method=None, axes_cmap='Greens')
res_df['Resampling'] = 'Original'
res_df['Tuning'] = 'Tuned'
all_results.append(res_df)
```

```
Training Logistic Regression (original)…
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best parameters: {'C': 100, 'class_weight': 'balanced', 'solver': 'liblinear'}
Best CV score: 0.7446
Saved Logistic_Regression_original to
```

```
../models/Logistic_Regression_original_model.pkl

Training Random Forest (original)…
Fitting 3 folds for each of 54 candidates, totalling 162 fits

/Users/santoshkumar/envs/ai/lib/python3.11/site-
packages/joblib/externals/loky/process_executor.py:782: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(

Best parameters: {'class_weight': 'balanced_subsample', 'max_depth': 10,
'min_samples_split': 2, 'n_estimators': 300}
Best CV score: 0.7467
Saved Random_Forest_original to ../models/Random_Forest_original_model.pkl

Training XG Boost Classifier (original)…
Fitting 3 folds for each of 162 candidates, totalling 486 fits
Best parameters: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 300,
'scale_pos_weight': 3, 'subsample': 0.8}
Best CV score: 0.7188
Saved XG_Boost_Classifier_original to
../models/XG_Boost_Classifier_original_model.pkl

Training Gradient Boosting Classifier (original)…
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Best parameters: {'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 200,
'subsample': 0.8}
Best CV score: 0.5754
Saved Gradient_Boosting_Classifier_original to
../models/Gradient_Boosting_Classifier_original_model.pkl
                         Model  Test Accuracy  Precision    Recall  F1-Score  \
3  Gradient Boosting Classifier       0.863213   0.829818  0.863213  0.833201
2          XG Boost Classifier       0.815437   0.854490  0.815437  0.830569
1                Random Forest       0.732931   0.866623  0.732931  0.772041
0          Logistic Regression       0.729659   0.864292  0.729659  0.769289

    ROC-AUC  Avg Precision
3  0.824097       0.399565
2  0.833676       0.430903
1  0.832213       0.428342
0  0.826169       0.403896
```



Logistic Regression (Acc: 0.73)
31577
12162
1554
5443
Random Forest (Acc: 0.73)
31678
12061
1489
5508
XG Boost Classifier (Acc: 0.82)
37222
6517
2847
4150
Gradient Boosting Classifier (Acc: 0.86)
42566
1173
5767
1230
True label
Predicted label
0
1



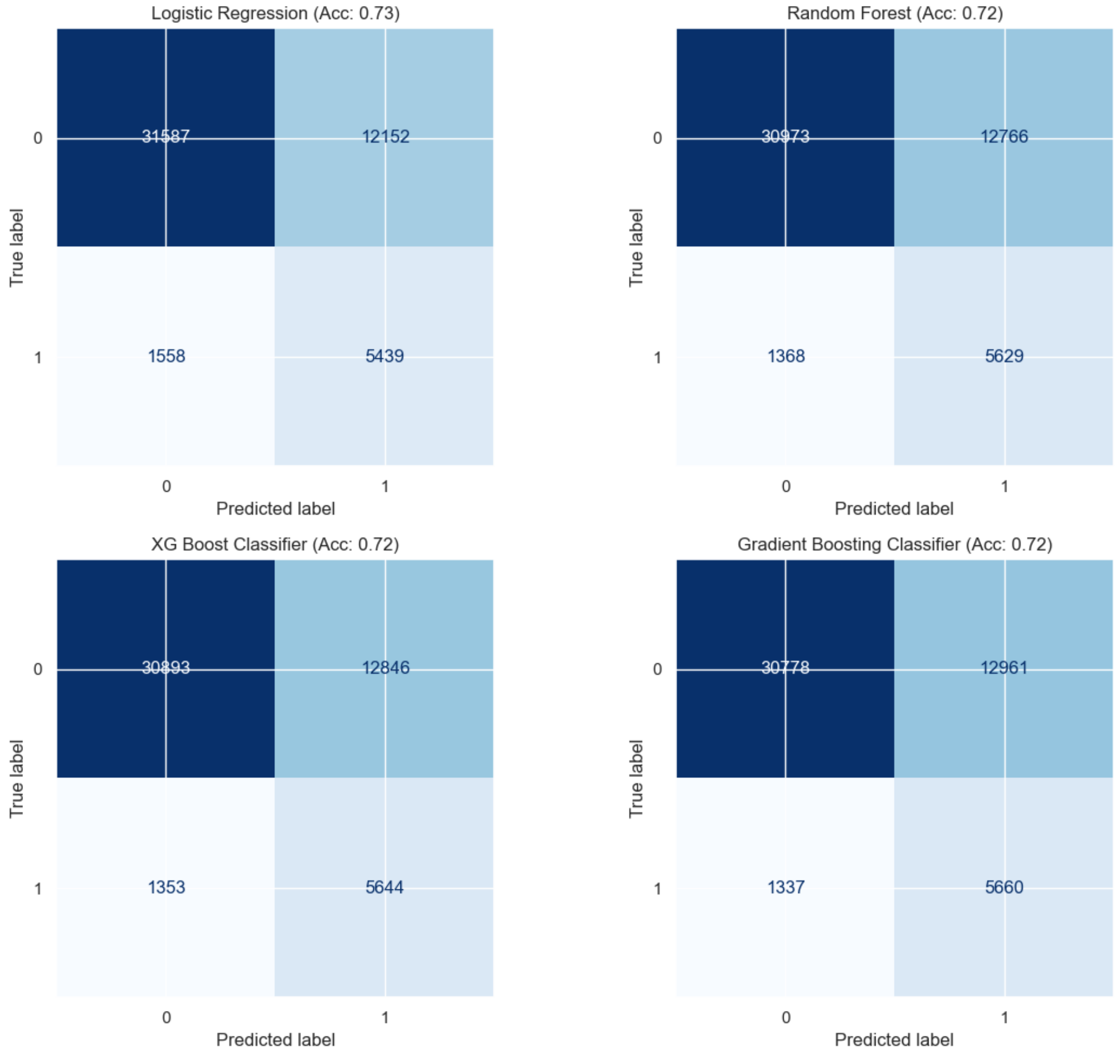
2.2.10 Training model with Undersampling

[16]:
```
res_df, _ = model_training_with_tuning(X_train, y_train, X_test, y_test,␣
    ↪resample_method='under', axes_cmap='Blues')
res_df['Resampling'] = 'Under'
res_df['Tuning'] = 'Tuned'
all_results.append(res_df)
```

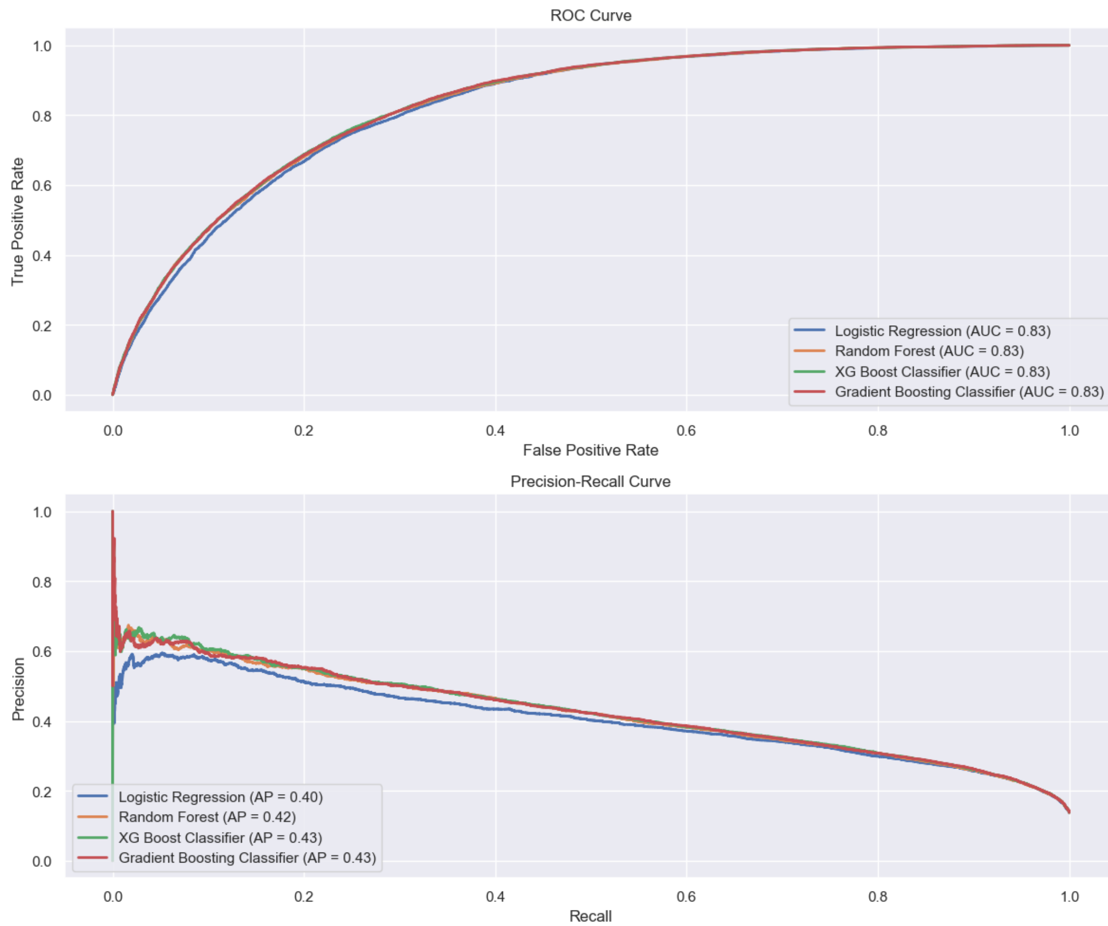
```
Training Logistic Regression (resampled)…
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best parameters: {'C': 10, 'class_weight': 'balanced', 'solver': 'liblinear'}
Best CV score: 0.7440
Saved Logistic_Regression_resampled_under to
../models/Logistic_Regression_resampled_under_model.pkl

Training Random Forest (resampled)…
Fitting 3 folds for each of 54 candidates, totalling 162 fits
```

```
/Users/santoshkumar/envs/ai/lib/python3.11/site-
packages/joblib/externals/loky/process_executor.py:782: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Best parameters: {'class_weight': 'balanced_subsample', 'max_depth': 10,
'min_samples_split': 2, 'n_estimators': 300}
Best CV score: 0.7475
Saved Random_Forest_resampled_under to
../models/Random_Forest_resampled_under_model.pkl

Training XG Boost Classifier (resampled)…
Fitting 3 folds for each of 162 candidates, totalling 486 fits
Best parameters: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100,
'scale_pos_weight': 1, 'subsample': 0.8}
Best CV score: 0.7489
Saved XG_Boost_Classifier_resampled_under to
../models/XG_Boost_Classifier_resampled_under_model.pkl

Training Gradient Boosting Classifier (resampled)…
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Best parameters: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 100,
'subsample': 0.8}
Best CV score: 0.7494
Saved Gradient_Boosting_Classifier_resampled_under to
../models/Gradient_Boosting_Classifier_resampled_under_model.pkl
                          Model  Test Accuracy  Precision    Recall  F1-Score  \
0           Logistic Regression       0.729778   0.864208  0.729778  0.769375
1                 Random Forest       0.721421   0.867826  0.721421  0.763077
2           XG Boost Classifier       0.720140   0.868014  0.720140  0.762074
3  Gradient Boosting Classifier       0.718188   0.868119  0.718188  0.760531

    ROC-AUC  Avg Precision
0  0.826145       0.403732
1  0.831684       0.423721
2  0.833451       0.427346
3  0.833096       0.425647
```



Logistic Regression (Acc: 0.73)
31587
12152
1558
5439
Random Forest (Acc: 0.72)
30973
12766
1368
5629
XG Boost Classifier (Acc: 0.72)
30893
12846
1353
5644
Gradient Boosting Classifier (Acc: 0.72)
30778
12961
1337
5660
True label
Predicted label
0
1



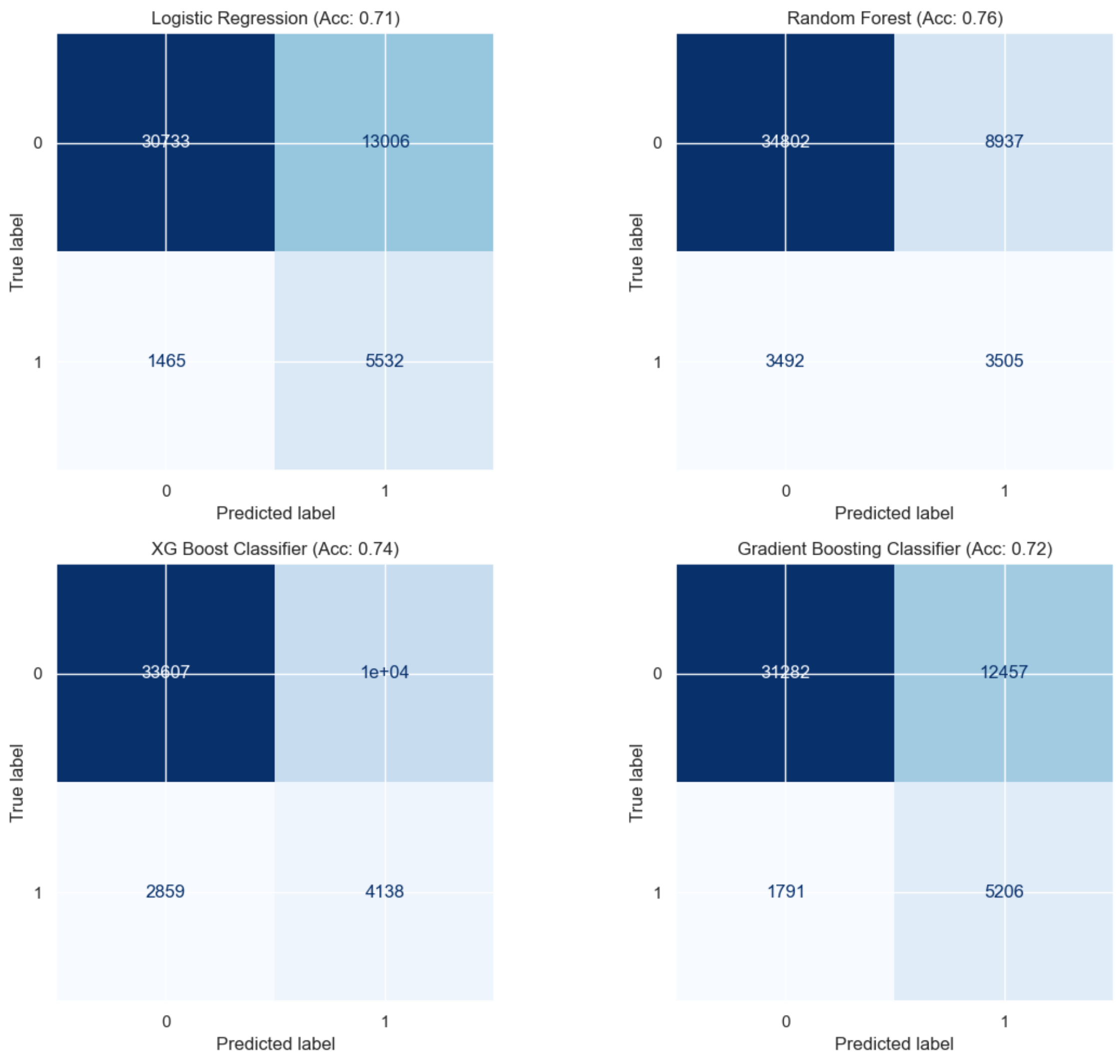
2.2.11 Training model with SMOTE Oversampling

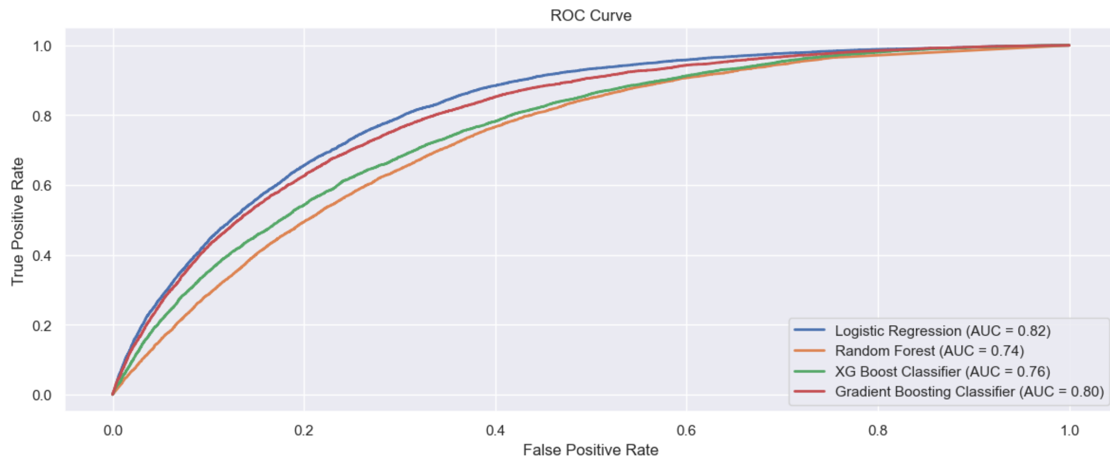
[17]:
```
res_df, _ = model_training_with_tuning(X_train, y_train, X_test, y_test,␣
    ↪resample_method='smote', axes_cmap='Purples')
res_df['Resampling'] = 'SMOTE'
res_df['Tuning'] = 'Tuned'
all_results.append(res_df)
```

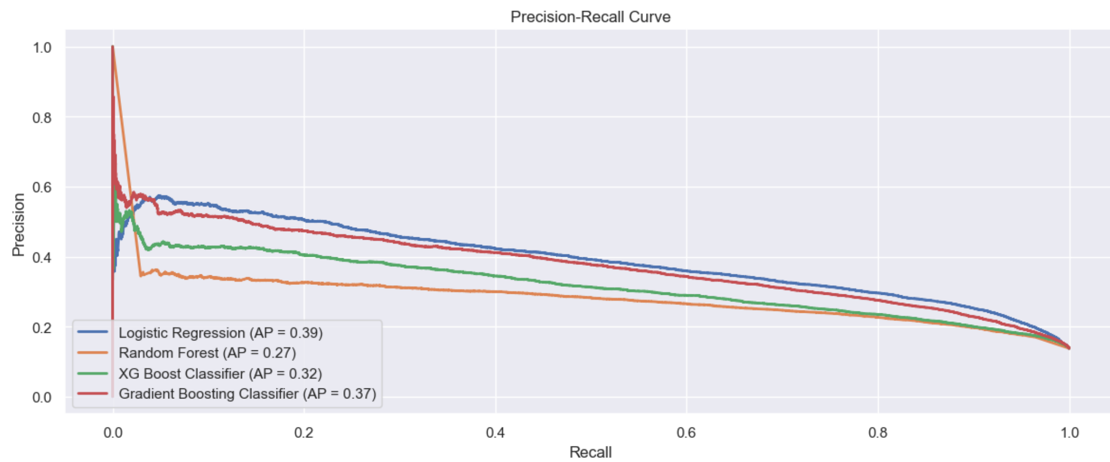
```
Training Logistic Regression (resampled)…
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best parameters: {'C': 100, 'class_weight': 'balanced', 'solver': 'lbfgs'}
Best CV score: 0.7285
Saved Logistic_Regression_resampled_smote to
../models/Logistic_Regression_resampled_smote_model.pkl

Training Random Forest (resampled)…
Fitting 3 folds for each of 54 candidates, totalling 162 fits
```

```
/Users/santoshkumar/envs/ai/lib/python3.11/site-
packages/joblib/externals/loky/process_executor.py:782: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Best parameters: {'class_weight': 'balanced', 'max_depth': None,
'min_samples_split': 2, 'n_estimators': 200}
Best CV score: 0.8299
Saved Random_Forest_resampled_smote to
../models/Random_Forest_resampled_smote_model.pkl

Training XG Boost Classifier (resampled)…
Fitting 3 folds for each of 162 candidates, totalling 486 fits
Best parameters: {'learning_rate': 0.2, 'max_depth': 10, 'n_estimators': 300,
'scale_pos_weight': 1, 'subsample': 0.8}
Best CV score: 0.8077
Saved XG_Boost_Classifier_resampled_smote to
../models/XG_Boost_Classifier_resampled_smote_model.pkl

Training Gradient Boosting Classifier (resampled)…
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Best parameters: {'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 200,
'subsample': 0.8}
Best CV score: 0.7652
Saved Gradient_Boosting_Classifier_resampled_smote to
../models/Gradient_Boosting_Classifier_resampled_smote_model.pkl
                          Model  Test Accuracy  Precision    Recall  F1-Score  \
1                 Random Forest       0.755026   0.822327  0.755026  0.781205
2          XG Boost Classifier       0.743949   0.834492  0.743949  0.776123
3  Gradient Boosting Classifier       0.719174   0.856053  0.719174  0.760408
0          Logistic Regression       0.714778   0.864019  0.714778  0.757560

    ROC-AUC  Avg Precision
1  0.737856       0.274315
2  0.760215       0.317412
3  0.801388       0.374479
0  0.818402       0.391368
```


Logistic Regression (Acc: 0.71)
30733
13006
1465
5532
True label
Predicted label
0
1
Random Forest (Acc: 0.76)
34802
8937
3492
3505
XG Boost Classifier (Acc: 0.74)
33607
1e+04
2859
4138
Gradient Boosting Classifier (Acc: 0.72)
31282
12457
1791
5206



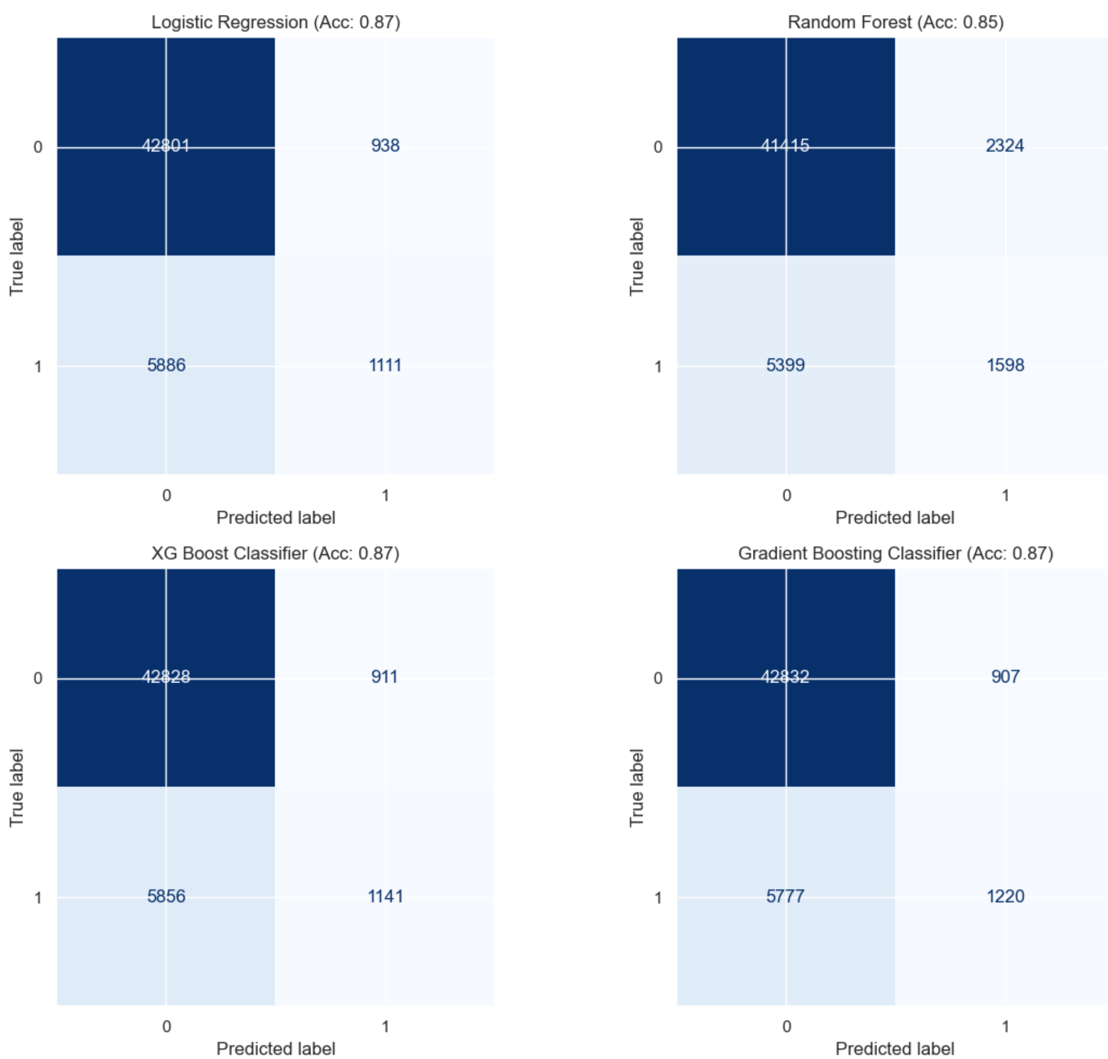


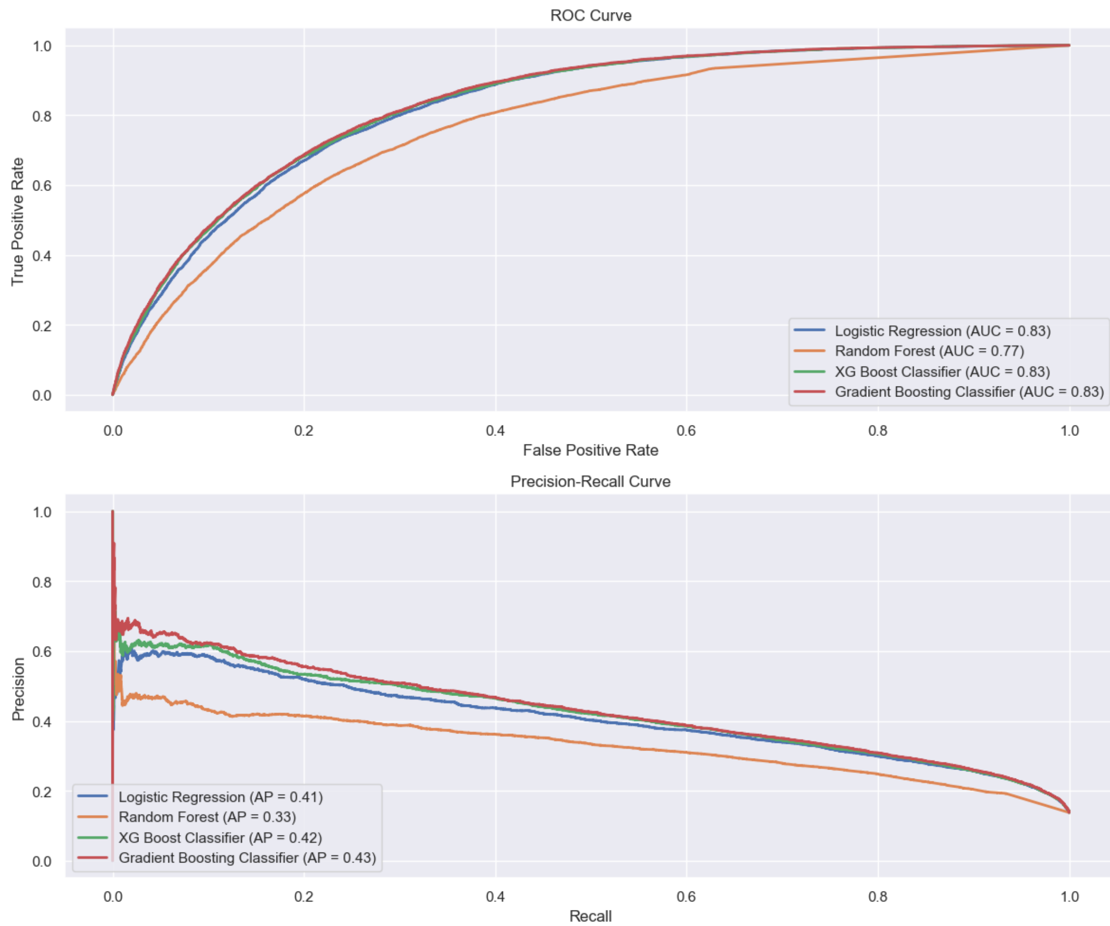
2.2.12 Training model NO TUNING (original)

[18]:
```
res_df, _ = model_training_with_no_tuning(X_train, y_train, X_test, y_test,␣
  ↪resample_method=None, axes_cmap='Oranges')
res_df['Resampling'] = 'Original'
res_df['Tuning'] = 'No Tuning'
all_results.append(res_df)
```

```
Training Logistic Regression (no tuning, original)…
Saved Logistic_Regression_no_tuning_original to
../models/Logistic_Regression_no_tuning_original_model.pkl

Training Random Forest (no tuning, original)…
Saved Random_Forest_no_tuning_original to
../models/Random_Forest_no_tuning_original_model.pkl

Training XG Boost Classifier (no tuning, original)…
```

```
Saved XG_Boost_Classifier_no_tuning_original to
../models/XG_Boost_Classifier_no_tuning_original_model.pkl

Training Gradient Boosting Classifier (no tuning, original)…
Saved Gradient_Boosting_Classifier_no_tuning_original to
../models/Gradient_Boosting_Classifier_no_tuning_original_model.pkl
                          Model  Test Accuracy  Precision    Recall  F1-Score  \
3  Gradient Boosting Classifier       0.868259   0.838736  0.868259  0.836574
2            XG Boost Classifier       0.866623   0.835077  0.866623  0.833748
0            Logistic Regression       0.865500   0.832645  0.865500  0.832315
1                  Random Forest       0.847781   0.818857  0.847781  0.828931

    ROC-AUC  Avg Precision
3  0.833852       0.431416
2  0.831047       0.422183
0  0.825852       0.405894
1  0.768715       0.326992
```



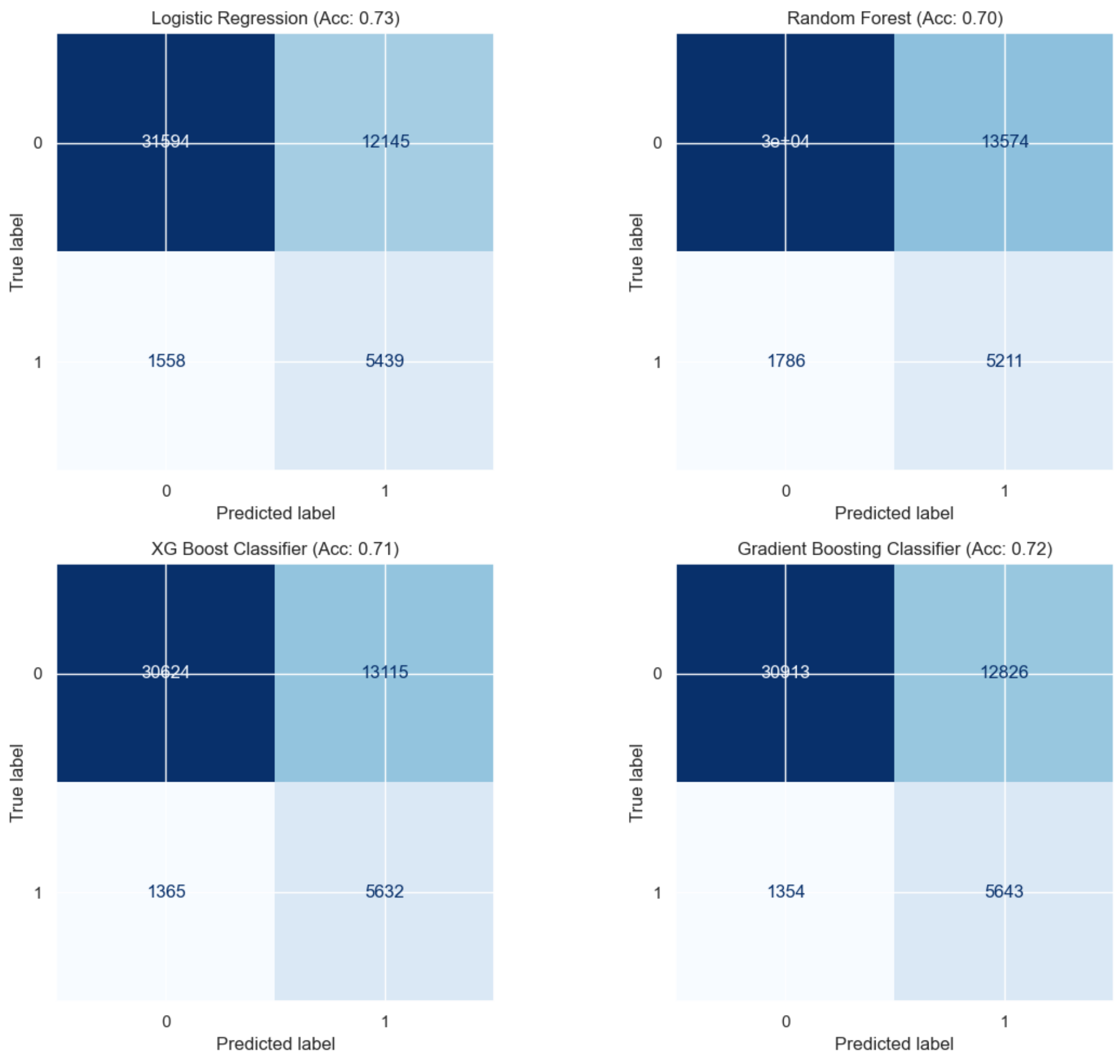


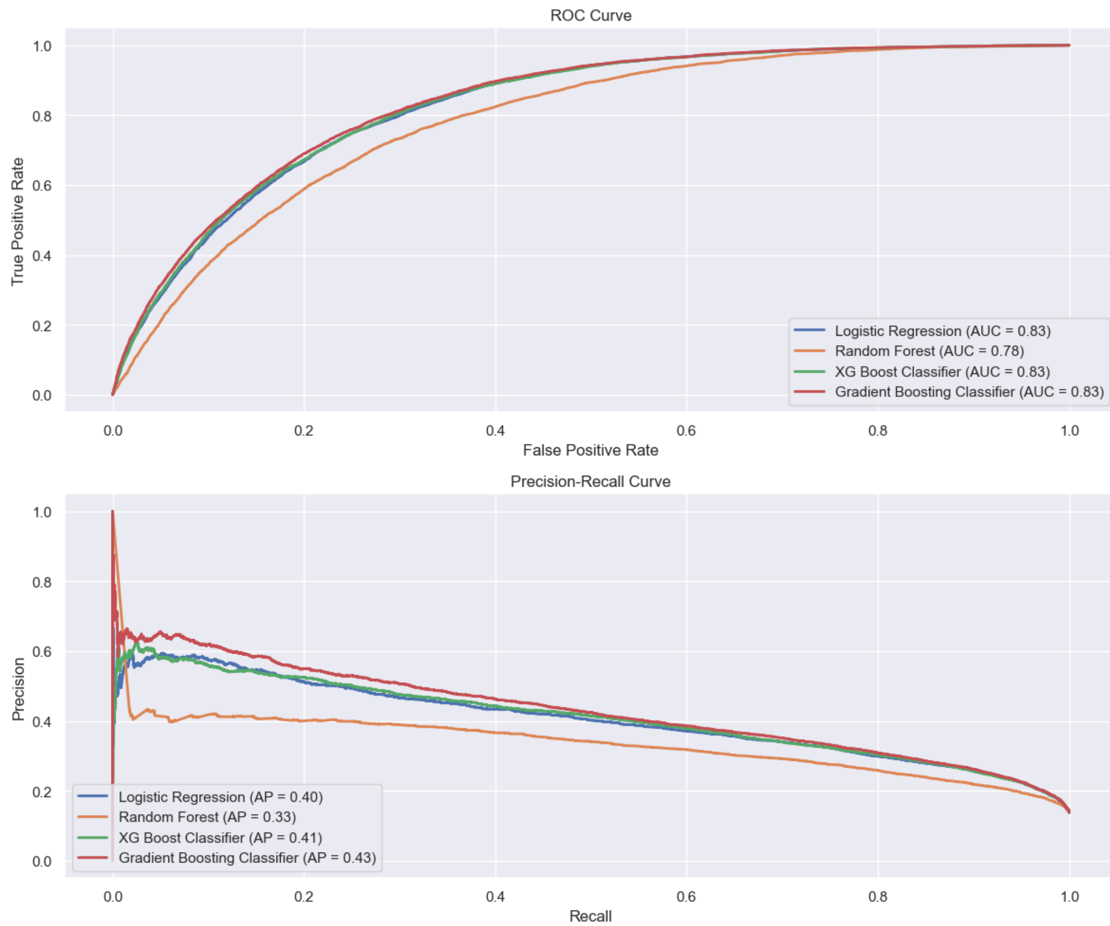
2.2.13 Training model NO TUNING (undersampling)

[19]:
```
res_df, _ = model_training_with_no_tuning(X_train, y_train, X_test, y_test,␣
  ↪resample_method='under', axes_cmap='Reds')
res_df['Resampling'] = 'Under'
res_df['Tuning'] = 'No Tuning'
all_results.append(res_df)
```

```
Training Logistic Regression (no tuning, resampled)…
Saved Logistic_Regression_no_tuning_resampled_under to
../models/Logistic_Regression_no_tuning_resampled_under_model.pkl

Training Random Forest (no tuning, resampled)…
Saved Random_Forest_no_tuning_resampled_under to
../models/Random_Forest_no_tuning_resampled_under_model.pkl
```

```
Training XG Boost Classifier (no tuning, resampled)…
Saved XG_Boost_Classifier_no_tuning_resampled_under to
../models/XG_Boost_Classifier_no_tuning_resampled_under_model.pkl

Training Gradient Boosting Classifier (no tuning, resampled)…
Saved Gradient_Boosting_Classifier_no_tuning_resampled_under to
../models/Gradient_Boosting_Classifier_no_tuning_resampled_under_model.pkl
                          Model  Test Accuracy  Precision    Recall  F1-Score  \
0           Logistic Regression       0.729916   0.864233  0.729916  0.769484
3  Gradient Boosting Classifier       0.720514   0.868052  0.720514  0.762374
2           XG Boost Classifier       0.714601   0.866735  0.714601  0.757590
1                 Random Forest       0.697256   0.852157  0.697256  0.742892

    ROC-AUC  Avg Precision
0  0.826143       0.403705
3  0.833664       0.428798
2  0.828054       0.408295
1  0.784448       0.329619
```


Logistic Regression (Acc: 0.73)
31594
12145
1558
5439
Random Forest (Acc: 0.70)
3e+04
13574
1786
5211
XG Boost Classifier (Acc: 0.71)
30624
13115
1365
5632
Gradient Boosting Classifier (Acc: 0.72)
30913
12826
1354
5643
True label
Predicted label
0
1

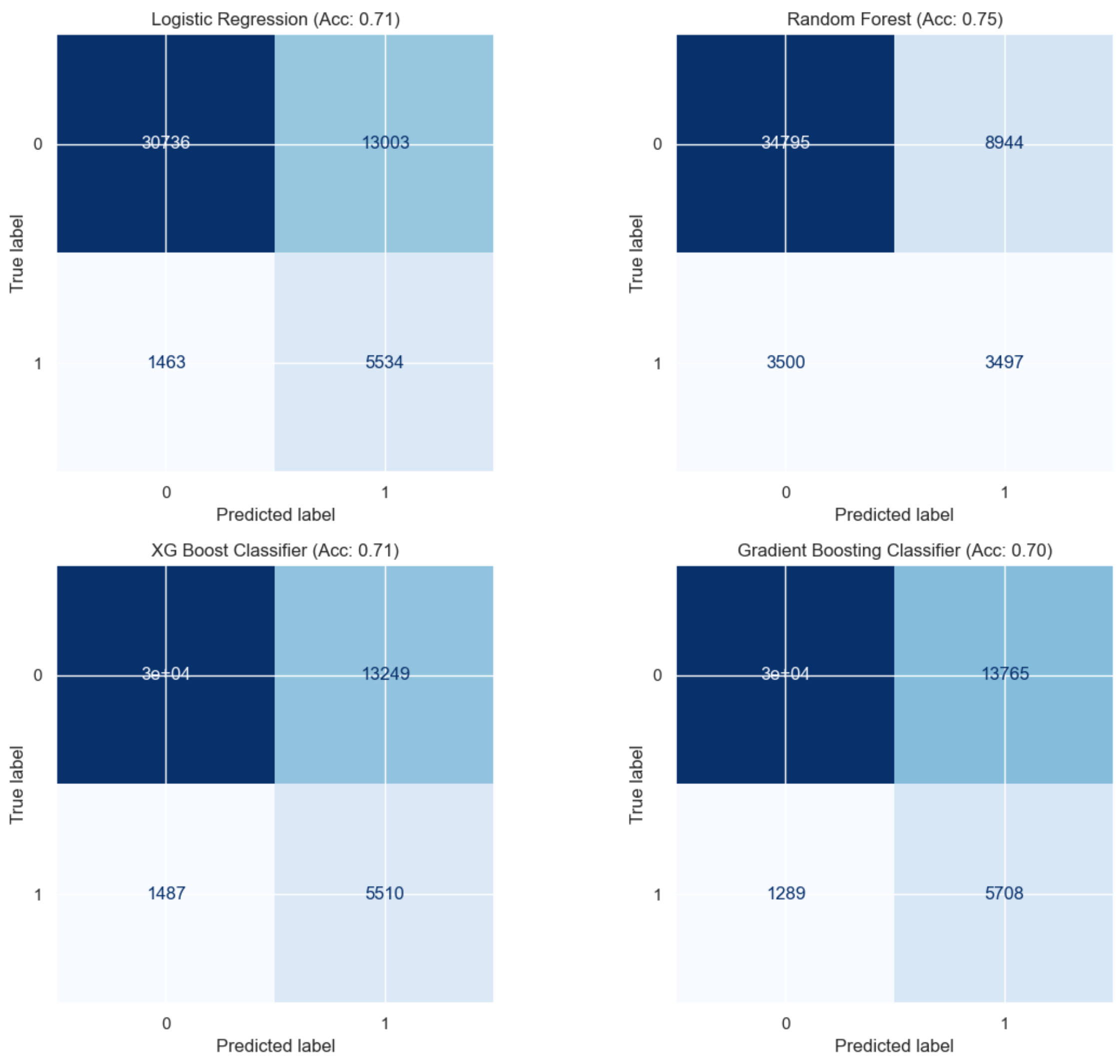


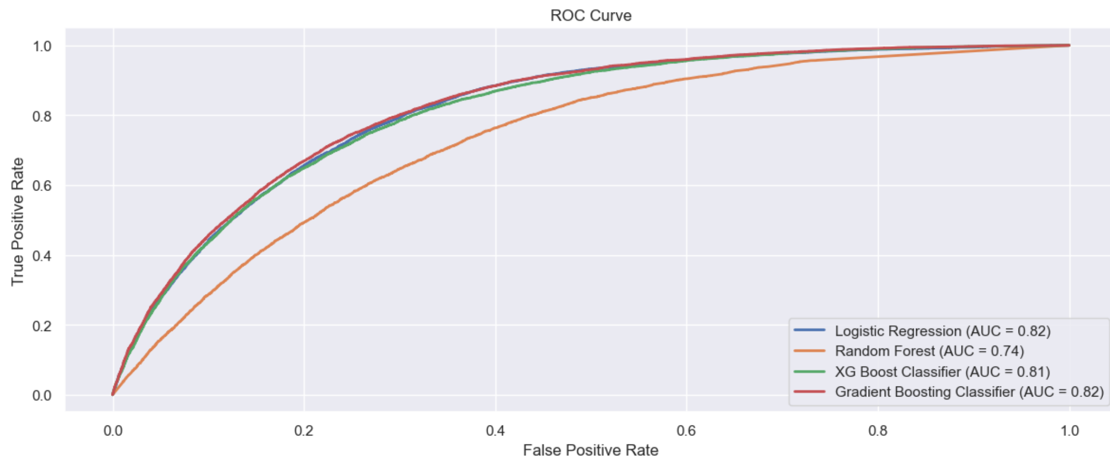
2.2.14 Training model NO TUNING (SMOTE)

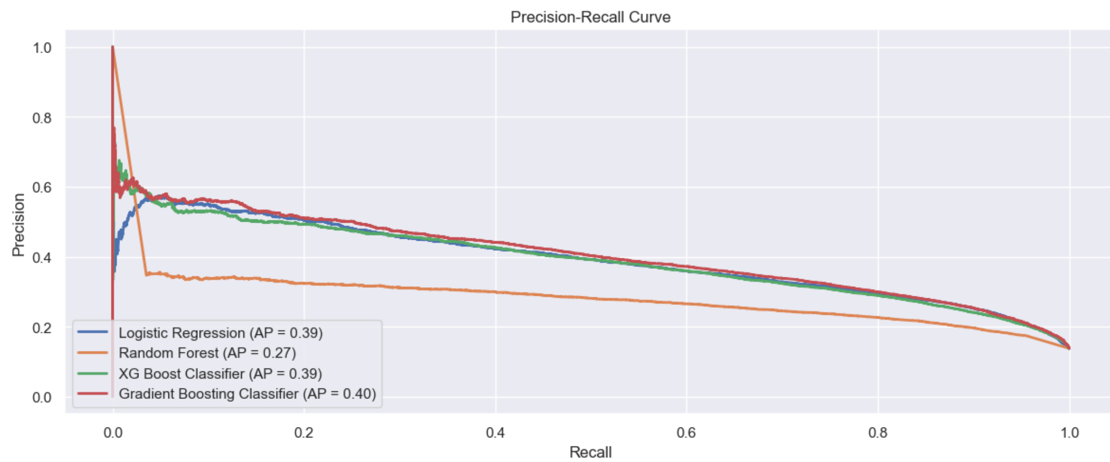
[20]:
```
res_df, _ = model_training_with_no_tuning(X_train, y_train, X_test, y_test,␣
  ↪resample_method='smote', axes_cmap='Greys')
res_df['Resampling'] = 'SMOTE'
res_df['Tuning'] = 'No Tuning'
all_results.append(res_df)
```

```
Training Logistic Regression (no tuning, resampled)…
Saved Logistic_Regression_no_tuning_resampled_smote to
../models/Logistic_Regression_no_tuning_resampled_smote_model.pkl

Training Random Forest (no tuning, resampled)…
Saved Random_Forest_no_tuning_resampled_smote to
../models/Random_Forest_no_tuning_resampled_smote_model.pkl

Training XG Boost Classifier (no tuning, resampled)…
```

```
Saved XG_Boost_Classifier_no_tuning_resampled_smote to
../models/XG_Boost_Classifier_no_tuning_resampled_smote_model.pkl

Training Gradient Boosting Classifier (no tuning, resampled)…
Saved Gradient_Boosting_Classifier_no_tuning_resampled_smote to
../models/Gradient_Boosting_Classifier_no_tuning_resampled_smote_model.pkl
                          Model  Test Accuracy  Precision    Recall  F1-Score  \
1                 Random Forest       0.754730   0.822063  0.754730  0.780938
0           Logistic Regression       0.714877   0.864091  0.714877  0.757643
2            XG Boost Classifier       0.709555   0.862509  0.709555  0.753315
3  Gradient Boosting Classifier       0.703288   0.866970  0.703288  0.748534

    ROC-AUC  Avg Precision
1  0.736533       0.273552
0  0.818376       0.391358
2  0.814232       0.389631
3  0.823528       0.404243
```







Finally, all the numbers come together in our results table. This table lists out every model we tried—Logistic Regression, Random Forest, XGBoost, and Gradient Boosting—under all the different training scenarios, like original data, undersampling, SMOTE, with and without tuning. It shows each one's accuracy, precision, recall, F1-score, ROC-AUC, and more. What's really helpful here is how you can instantly spot which setup performed best—like Gradient Boosting on the original, unbalanced data with no tuning, hitting 86.8% accuracy and an AUC of 0.83.

[21]:
```
final_results_df = pd.concat(all_results, ignore_index=True)
final_results_df.sort_values(by='Test Accuracy', ascending=False, inplace=True)
display(final_results_df)
```

```
                           Model  Test Accuracy  Precision    Recall  \
15  Gradient Boosting Classifier       0.868259   0.838736  0.868259
14            XG Boost Classifier      0.866623   0.835077  0.866623
12            Logistic Regression      0.865500   0.832645  0.865500
3   Gradient Boosting Classifier       0.863213   0.829818  0.863213
13                  Random Forest      0.847781   0.818857  0.847781
```

2	XG Boost Classifier	0.815437	0.854490	0.815437
9	Random Forest	0.755026	0.822327	0.755026
21	Random Forest	0.754730	0.822063	0.754730
10	XG Boost Classifier	0.743949	0.834492	0.743949
1	Random Forest	0.732931	0.866623	0.732931
16	Logistic Regression	0.729916	0.864233	0.729916
4	Logistic Regression	0.729778	0.864208	0.729778
0	Logistic Regression	0.729659	0.864292	0.729659
5	Random Forest	0.721421	0.867826	0.721421
19	Gradient Boosting Classifier	0.720514	0.868052	0.720514
6	XG Boost Classifier	0.720140	0.868014	0.720140
11	Gradient Boosting Classifier	0.719174	0.856053	0.719174
7	Gradient Boosting Classifier	0.718188	0.868119	0.718188
20	Logistic Regression	0.714877	0.864091	0.714877
8	Logistic Regression	0.714778	0.864019	0.714778
18	XG Boost Classifier	0.714601	0.866735	0.714601
22	XG Boost Classifier	0.709555	0.862509	0.709555
23	Gradient Boosting Classifier	0.703288	0.866970	0.703288
17	Random Forest	0.697256	0.852157	0.697256

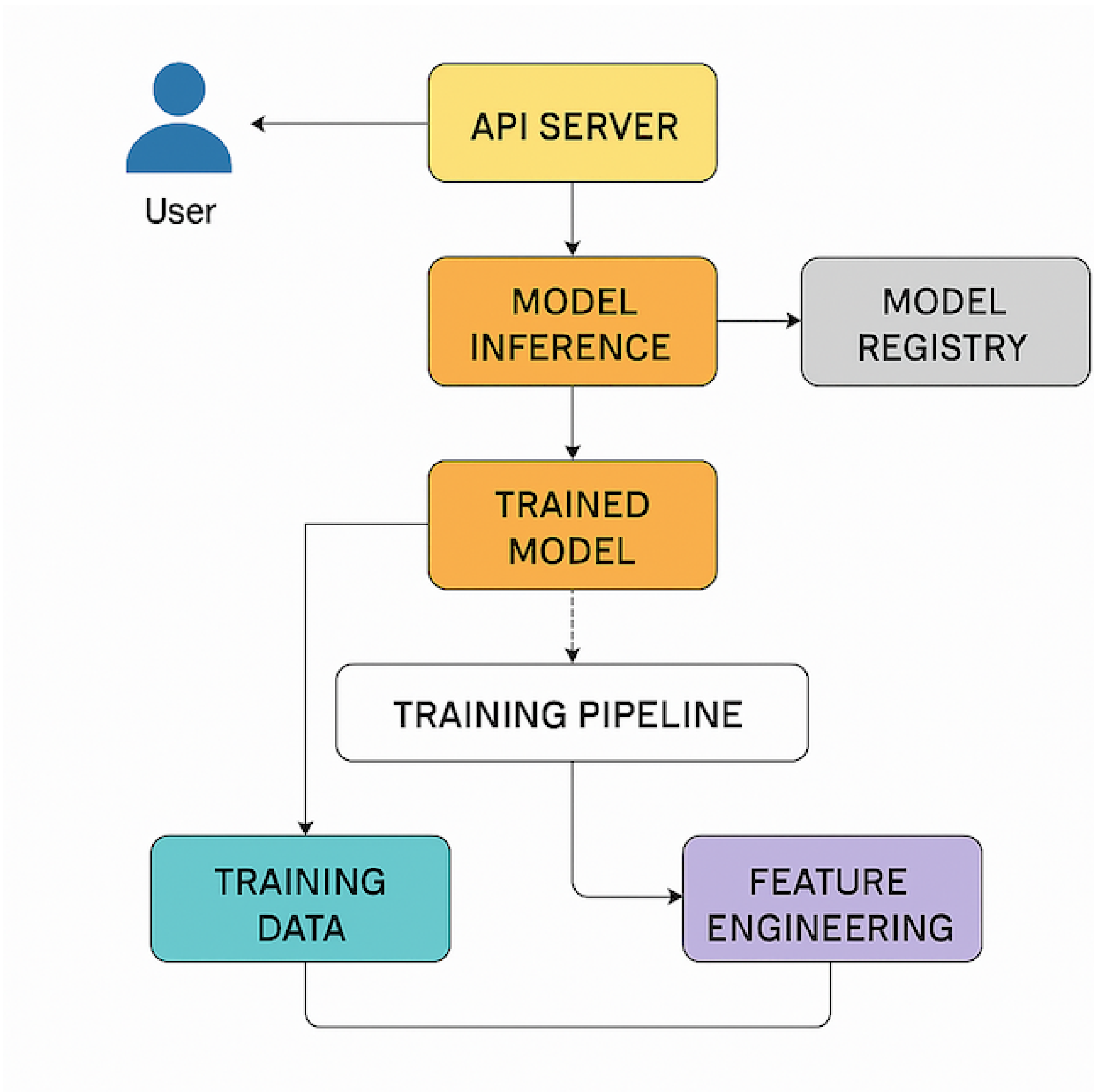
	F1-Score	ROC-AUC	Avg Precision	Resampling	Tuning
15	0.836574	0.833852	0.431416	Original	No Tuning
14	0.833748	0.831047	0.422183	Original	No Tuning
12	0.832315	0.825852	0.405894	Original	No Tuning
3	0.833201	0.824097	0.399565	Original	Tuned
13	0.828931	0.768715	0.326992	Original	No Tuning
2	0.830569	0.833676	0.430903	Original	Tuned
9	0.781205	0.737856	0.274315	SMOTE	Tuned
21	0.780938	0.736533	0.273552	SMOTE	No Tuning
10	0.776123	0.760215	0.317412	SMOTE	Tuned
1	0.772041	0.832213	0.428342	Original	Tuned
16	0.769484	0.826143	0.403705	Under	No Tuning
4	0.769375	0.826145	0.403732	Under	Tuned
0	0.769289	0.826169	0.403896	Original	Tuned
5	0.763077	0.831684	0.423721	Under	Tuned
19	0.762374	0.833664	0.428798	Under	No Tuning
6	0.762074	0.833451	0.427346	Under	Tuned
11	0.760408	0.801388	0.374479	SMOTE	Tuned
7	0.760531	0.833096	0.425647	Under	Tuned
20	0.757643	0.818376	0.391358	SMOTE	No Tuning
8	0.757560	0.818402	0.391368	SMOTE	Tuned
18	0.757590	0.828054	0.408295	Under	No Tuning
22	0.753315	0.814232	0.389631	SMOTE	No Tuning
23	0.748534	0.823528	0.404243	SMOTE	No Tuning
17	0.742892	0.784448	0.329619	Under	No Tuning

2.2.15 Model Deployment

Now it's time to deploy a trained model. Model is deployed and used in production, as shown in this diagram.

1. The process begins with the user which could be a real person or another application—interacting with an API server.
2. This server acts as the gateway, receiving the user's input data and passing it along to the model inference component, where the actual prediction happens using a trained model.
3. The model inference step is powered by the latest version of the trained model, which is registered and tracked in the model registry for version control and easy updates.
4. Behind the scenes, whenever we want to improve the model, the training pipeline kicks in. It takes in new training data, processes it with feature engineering to create better inputs, and retrains the model as needed.
5. The newly trained model is then sent back to the registry and used for future inferences.

This pipeline ensures that user inputs flow smoothly all the way from the user interface to a smart prediction and back, while keeping the system flexible, updatable, and robust for real-world use.



2.2.16 Discussion and conclusions

In this project, we set out to address the serious challenge of underdiagnosed and costly diabetes in the United States by building a machine learning model capable of predicting diabetes risk based on widely available CDC health indicators. Our results show that modern ML models, especially Gradient Boosting and XGBoost, are effective at detecting diabetes risk even when trained on real-world, highly imbalanced datasets. Through systematic experiments with data balancing (using undersampling and SMOTE) and hyperparameter tuning, we found that Gradient Boosting performed best, achieving a test accuracy of 86.8% and a strong ROC-AUC of 0.83 on the original unbalanced dataset, even without parameter tuning.

The analysis of our model's confusion matrices, ROC curves, and precision-recall curves demonstrates that our solution can detect a significant portion of true diabetes cases while controlling for false positives—a crucial balance in healthcare. However, the moderate average precision score (around 0.43) also highlights the ongoing challenge of identifying rare cases in a sea of healthy individuals. Data imbalance remains a critical issue in this domain, but resampling methods like

SMOTE and robust ensemble algorithms help mitigate its effects.

We recommend that healthcare providers and public health organizations consider integrating such predictive models into their workflows, particularly for early screening and outreach programs. The model can be exposed as an API and deployed in cloud-native environments for real-time risk prediction, as demonstrated in our deployment pipeline. For future work, we suggest periodic retraining of the model with new data and continuous monitoring of prediction quality to ensure long-term effectiveness. Ultimately, predictive analytics like this have strong potential to complement traditional screening, prioritize high-risk individuals, and help reduce the overall burden of diabetes in society.