```
# 1. Imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import time
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, fbeta_score, classification_report,
                             confusion_matrix, ConfusionMatrixDisplay)
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import make pipeline as make pipeline imb
# Load the New Dataset #2
# dataset 2
import pandas as pd # Use pd instead of pd2
# Correct RAW URL
url = "https://raw.githubusercontent.com/AsmaShaikhTMU/Projects/main/diabetes_012_health_indicators_BRFSS2015.csv"
# Read CSV file
df2 = pd.read csv(url)
# Display first few rows
df2.head()
```

_		Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	Fruits	 AnyHealthcare	NoDocł
	0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	0.0	0.0	 1.0	
	1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	1.0	0.0	 0.0	
	2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	0.0	1.0	 1.0	
	3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	1.0	1.0	 1.0	
	4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	1.0	1.0	 1.0	
5 rows × 22 columns													
	4 =												•

```
# 1. Inspect the Data
df2.info()
df2.describe()
df2['Diabetes_012'].value_counts() # this is your target column
```

```
→ <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 253680 entries, 0 to 253679
     Data columns (total 22 columns):
     # Column
                               Non-Null Count
                                                 Dtype
                                _____
     0
          Diabetes_012
                                253680 non-null
                                                 float64
         HighBP
                                253680 non-null float64
      2
         HighChol
                                253680 non-null float64
          CholCheck
                                253680 non-null
                                253680 non-null float64
          BMI
          Smoker
                                253680 non-null float64
          Stroke
                                253680 non-null
                                                 float64
          HeartDiseaseorAttack 253680 non-null float64
      8
         PhysActivity
                                253680 non-null float64
          Fruits
                                253680 non-null
                                                 float64
      10 Veggies
                                253680 non-null
         HvyAlcoholConsump
                                253680 non-null
                                                 float64
      11
     12 AnyHealthcare
                                253680 non-null float64
      13 NoDocbcCost
                                253680 non-null float64
      14 GenHlth
                                253680 non-null
                                                 float64
      15 MentHlth
                                253680 non-null float64
      16 PhysHlth
                                253680 non-null float64
      17 DiffWalk
                                253680 non-null
     18 Sex
                                253680 non-null float64
      19 Age
                                253680 non-null float64
      20 Education
                                253680 non-null float64
     21 Income
                                253680 non-null float64
     dtypes: float64(22)
     memory usage: 42.6 MB
      Diabetes_012
          0.0
                    213703
          2.0
                     35346
          1.0
                      4631
     dtvne: int64
# Combine 0 and 1 (no diabetes + prediabetes) \rightarrow 0, and diabetes (2) \rightarrow 1
df2['Diabetes_012'] = df2['Diabetes_012'].replace({1.0: 1, 2.0: 1})
print(df2['Diabetes_012'].value_counts())
\rightarrow
   Diabetes_012
     0.0
            213703
     1.0
            39977
     Name: count, dtype: int64
The column Diabetes_012 has 3 classes:
0: no diabetes
1: prediabetes
2: diabetes
# Display dataset info (column types, null values, memory usage)
print("\nDataset Info:")
df2.info()
# Check for duplicate rows
duplicate_count = df2.duplicated().sum()
```

duplicate_percent = (duplicate_count / len(df2)) * 100
print(f"\nDuplicate Rows Count: {duplicate_count}")
print(f"Percentage of Duplicates: {duplicate_percent:.2f}%")

print(f"\nTotal Missing Values in Dataset: {total_missing}")

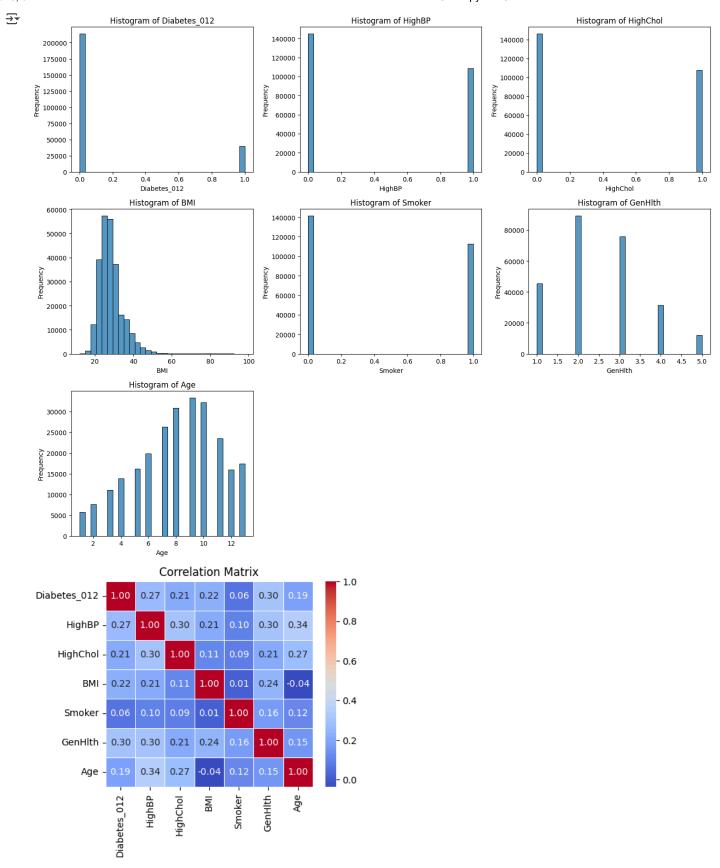
Print missing values per column
missing_per_column = df2.isnull().sum()
total_missing = missing_per_column.sum()

```
Dataset Info:
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 253680 entries, 0 to 253679
    Data columns (total 22 columns):
     # Column
                              Non-Null Count
                                               Dtype
                              -----
                            253680 non-null float64
     0
         Diabetes_012
         HighBP
                              253680 non-null float64
         HighChol
                              253680 non-null float64
         CholCheck
                              253680 non-null float64
         BMI
                              253680 non-null float64
                              253680 non-null float64
         Stroke
                              253680 non-null float64
     6
         HeartDiseaseorAttack 253680 non-null float64
         PhysActivity
                              253680 non-null float64
         Fruits
                              253680 non-null float64
     10 Veggies
                              253680 non-null float64
     11 HvyAlcoholConsump
                              253680 non-null float64
                              253680 non-null float64
     12 AnyHealthcare
                              253680 non-null float64
     13 NoDocbcCost
     14 GenHlth
                              253680 non-null float64
         MentHlth
                              253680 non-null float64
     16 PhysHlth
                              253680 non-null float64
                              253680 non-null float64
     17 DiffWalk
     18 Sex
                              253680 non-null float64
     19 Age
                              253680 non-null float64
                              253680 non-null float64
     20 Education
     21 Income
                              253680 non-null float64
    dtypes: float64(22)
    memory usage: 42.6 MB
    Duplicate Rows Count: 23968
    Percentage of Duplicates: 9.45%
    Total Missing Values in Dataset: 0
df2 = df2.drop_duplicates()
print(" ☑ Duplicates removed.")
print("Remaining rows:", len(df2))
     ☑ Duplicates removed.
    Remaining rows: 229712
# List of columns you want to keep
columns_to_keep = [
    'Diabetes_012', 'HighBP', 'HighChol', 'BMI', 'Smoker',
    'GenHlth', 'Age'
]
# Keep only those columns in df2
df2 = df2[columns_to_keep]
# Display summary statistics of numerical columns
print("\nSummary Statistics:")
display(df2.describe())
    Summary Statistics:
```

-							
	Diabetes_012	HighBP	HighChol	BMI	Smoker	GenHlth	Age
count	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000	253680.000000
mean	0.157588	0.429001	0.424121	28.382364	0.443169	2.511392	8.032119
std	0.364355	0.494934	0.494210	6.608694	0.496761	1.068477	3.054220
min	0.000000	0.000000	0.000000	12.000000	0.000000	1.000000	1.000000
25%	0.000000	0.000000	0.000000	24.000000	0.000000	2.000000	6.000000
50%	0.000000	0.000000	0.000000	27.000000	0.000000	2.000000	8.000000
75%	0.000000	1.000000	1.000000	31.000000	1.000000	3.000000	10.000000
max	1.000000	1.000000	1.000000	98.000000	1.000000	5.000000	13.000000

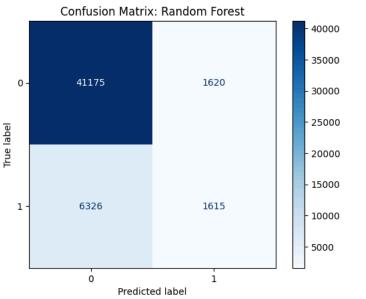
RF MODEL BASELINE

```
import seaborn as sns
import matplotlib.pyplot as plt
# List of selected columns
columns_to_plot = ['Diabetes_012', 'HighBP', 'HighChol', 'BMI', 'Smoker', 'GenHlth', 'Age']
# Histograms (all in one figure)
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15, 12))
axes = axes.flatten()
for i, col in enumerate(columns_to_plot):
    sns.histplot(df2[col], bins=30, kde=False, ax=axes[i], edgecolor='black')
    axes[i].set_title(f'Histogram of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Frequency')
for j in range(len(columns_to_plot), len(axes)):
    fig.delaxes(axes[j])
plt.tight_layout()
plt.show()
# Correlation heatmap
correlation_matrix = df2[columns_to_plot].corr()
plt.figure(figsize=(5, 4))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



```
# Calculate percentage of individuals with BMI > 30 who have diabetes (Diabetes_012 == 2)
diabetic_bmi = df2[(df2['BMI'] > 30) & (df2['Diabetes_012'] == 1)].shape[0]
total_bmi_above_30 = df2[df2['BMI'] > 30].shape[0]
if total_bmi_above_30 > 0:
    percentage_diabetic_bmi = (diabetic_bmi / total_bmi_above_30) * 100
    print(f"Percentage of individuals with BMI > 30 who have diabetes: {percentage_diabetic_bmi:.2f}%")
    print("No individuals with BMI > 30 in the dataset.")
Percentage of individuals with BMI > 30 who have diabetes: 27.68%
#High Blood Pressure (HighBP) vs Diabetes
diabetic_highbp = df2[(df2['HighBP'] == 1) & (df2['Diabetes_012'] == 1)].shape[0]
total_highbp = df2[df2['HighBP'] == 1].shape[0]
if total_highbp > 0:
    percentage_diabetic_highbp = (diabetic_highbp / total_highbp) * 100
    print(f"Percentage of individuals with HighBP who have diabetes: {percentage_diabetic_highbp:.2f}%")
else:
    print("No individuals with HighBP in the dataset.")
Percentage of individuals with HighBP who have diabetes: 27.12%
print(df2['Diabetes_012'].value_counts())
→ Diabetes_012
           213703
     0.0
     1.0
             39977
     Name: count, dtype: int64
#High Cholesterol (HighChol) vs Diabetes
diabetic highchol = df2[(df2['HighChol'] == 1) & (df2['Diabetes 012'] == 1)].shape[0]
total_highchol = df2[df2['HighChol'] == 1].shape[0]
if total_highchol > 0:
    percentage_diabetic_highchol = (diabetic_highchol / total_highchol) * 100
    print(f"Percentage of individuals with HighChol who have diabetes: {percentage_diabetic_highchol:.2f}%")
else:
    print("No individuals with HighChol in the dataset.")
Percentage of individuals with HighChol who have diabetes: 24.69%
Then continue with:
Train/test split
Preprocessing (scaling only – all columns are numeric here)
Model evaluation (Logistic, RF, etc.)
Cross-validation and tuning (just like you did in Dataset 1)
# 1. Define features and target
X = df2.drop(columns='Diabetes_012')
y = df2['Diabetes_012']
```

```
# 3. Split into train/test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# 4. Preprocessing pipeline (only scaling needed since all features are numeric)
preprocessor = ColumnTransformer([
    ("num", StandardScaler(), X.columns)
])
# 5. Define models
models = {
    #"Logistic Regression": LogisticRegression(max_iter=1000, random_state=42),
    #"Decision Tree": DecisionTreeClassifier(random_state=42),
    #"K-Nearest Neighbors": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier(random_state=42),
    #"Support Vector Machine": SVC(probability=True, random_state=42),
}
# 6. Evaluation function
def evaluate_model(name, model):
    pipeline = make_pipeline(preprocessor, model)
    cv_scores = cross_val_score(pipeline, X_train, y_train, cv=5, scoring='f1')
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    print(f"\nModel: {name}")
    print(f"Mean CV F1 Score: {cv_scores.mean():.4f}")
    print(classification_report(y_test, y_pred))
    cm = confusion_matrix(y_test, y_pred)
    ConfusionMatrixDisplay(confusion_matrix=cm).plot(cmap='Blues')
    plt.title(f"Confusion Matrix: {name}")
    plt.show()
# 7. Run evaluation for all models
for name, model in models.items():
    evaluate_model(name, model)
₹
     Model: Random Forest
     Mean CV F1 Score: 0.2868
                   precision
                                recall f1-score
                                                    support
              0.0
                        0.87
                                  0.96
                                             0.91
                                                      42795
                        0.50
                                             0.29
                                                       7941
              1.0
                                  9.29
                                             0.84
                                                      50736
         accuracy
                        0.68
                                  0.58
                                                      50736
        macro avg
                                             0.60
     weighted avg
                        0.81
                                  0.84
                                             0.81
                                                      50736
```



High precision for Logistic Regression (it's cautious, but misses a lot of diabetics = low recall).

Decision Tree is a bit more balanced, but still weak.

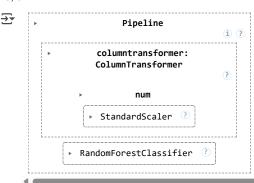
KNN is heavily biased toward the majority class (0.0 = No Diabetes)

RF Very high performance on class 0, but... Low recall on class 1 — meaning it's missing 83% of actual diabetes cases. This model, like others, is impacted by class imbalance.

TEST THE FINE TUNED RF MODEL

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
import pandas as pd
# Define features and target
X = df2.drop(columns='Diabetes_012')
y = df2['Diabetes_012']
# 1. Preprocessing: scale all features
preprocessor = ColumnTransformer([
    ("scaler", StandardScaler(), X.columns)
])
# 2. Pipeline with Random Forest
rf_pipeline = make_pipeline(preprocessor, RandomForestClassifier(random_state=42))
# 3. Hyperparameter grid
param_grid = {
    'randomforestclassifier__n_estimators': [50, 100, 200],
    'randomforestclassifier__max_depth': [None, 5, 10],
    'randomforestclassifier__min_samples_split': [2, 5]
}
# 4. GridSearchCV
grid_search = GridSearchCV(
    rf_pipeline,
    param_grid,
    cv=5,
    scoring='f1',
    n_jobs=-1,
    verbose=1
)
grid_search.fit(X_train, y_train)
# 5. Evaluate
best rf model = grid search.best estimator
y_pred_best = best_rf_model.predict(X_test)
print("\n ☑ Best Hyperparameters for Random Forest:")
print(grid_search.best_params_)
print("\n | Classification Report (Tuned Random Forest):")
print(classification_report(y_test, y_pred_best))
Fitting 5 folds for each of 18 candidates, totalling 90 fits
     ✓ Best Hyperparameters for Random Forest:
     {'randomforestclassifier_max_depth': None, 'randomforestclassifier_min_samples_split': 2, 'randomforestclassifier_n_estimators': 100}
     Classification Report (Tuned Random Forest):
                   precision
                                recall f1-score
                                                   support
              0.0
                        0.87
                                  0.96
                                            0.91
                                                      42795
                                                      7941
              1.0
                        0.50
                                  0.20
                                            0.29
         accuracy
                                            0.84
                                                      50736
        macro avg
                        0.68
                                  0.58
                                            0.60
                                                      50736
                                                      50736
     weighted avg
                        0.81
                                  0.84
                                            0.81
```

```
X = df2.drop("Diabetes_012", axis=1)
y = df2["Diabetes_012"]
# 2. Split the data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# 3. Set up preprocessor
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
categorical = X.select_dtypes(include='object').columns
numerical = X.select_dtypes(include='number').columns
preprocessor = ColumnTransformer([
    ("num", StandardScaler(), numerical),
    ("cat", OneHotEncoder(handle_unknown='ignore'), categorical)
])
# 4. Train pipeline with Random Forest
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
pipeline = make_pipeline(preprocessor, RandomForestClassifier(random_state=42))
pipeline.fit(X_train, y_train)
# 5. Extract feature importances
model = pipeline.named_steps['randomforestclassifier']
importances = model.feature_importances_
# 6. Get feature names
all_feature_names = list(numerical)
if categorical.any():
    encoder = pipeline.named steps['columntransformer'].named transformers ['cat']
    all_feature_names += list(encoder.get_feature_names_out(categorical))
# 7. Create importance DataFrame
importances_df = pd.DataFrame({
    'Feature': all feature names,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)
# 8. Show top 5 features
print(importances_df.head(5))
<del>_</del>_
         Feature Importance
             BMI
                    0.367629
     4
         GenHlth
                    0.223784
                    0.167143
             Age
          HighBP
                    0.156109
     1 HighChol
                    0.070791
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
# Define top 5 features again if needed
top_features = importances_df['Feature'].head(5).tolist()
X_top5 = X[top_features]
# Split the data
X_train_top5, X_test_top5, y_train_top5, y_test_top5 = train_test_split(X_top5, y, test_size=0.2, random_state=42)
# Preprocessing for top-5
simpler_preprocessor = ColumnTransformer([
    ("num", StandardScaler(), top_features)
])
# Define and train pipeline
simpler_pipeline = make_pipeline(simpler_preprocessor, RandomForestClassifier(random_state=42))
simpler_pipeline.fit(X_train_top5, y_train_top5)
```



#Compare performance (accuracy, F1) between full vs top-5 models from sklearn.metrics import accuracy_score, f1_score # Predictions y_pred_full = pipeline.predict(X_test) y_pred_top5 = simpler_pipeline.predict(X_test_top5) full_accuracy = accuracy_score(y_test, y_pred_full) full_f1 = f1_score(y_test, y_pred_full) top5_accuracy = accuracy_score(y_test_top5, y_pred_top5) top5_f1 = f1_score(y_test_top5, y_pred_top5) # Summary table import pandas as pd performance_comparison = pd.DataFrame({ "Model": ["Full Model", "Top-5 Model"], "Accuracy": [full_accuracy, top5_accuracy], "F1 Score": [full_f1, top5_f1] }) print(performance_comparison) Model Accuracy F1 Score Full Model 0.843385 0.289012 1 Top-5 Model 0.846500 0.281550 #Add GridSearchCV for tuning this simplified model # Do it for F2# # 🥕 2. Tune Top-5 Model with GridSearchCV import pandas as pd performance_comparison = pd.DataFrame(columns=["Model", "Accuracy", "F1", "F2"]) from sklearn.model_selection import GridSearchCV param_grid = { 'randomforestclassifier__n_estimators': [50, 100, 200], 'randomforestclassifier__max_depth': [None, 5, 10] } grid = GridSearchCV(simpler_pipeline, param_grid, cv=5, scoring='f1', n_jobs=-1) grid.fit(X_train_top5, y_train_top5) # Best model from grid search best_top5_pipeline = grid.best_estimator_ y_pred_top5_tuned = best_top5_pipeline.predict(X_test_top5) # Metrics tuned_accuracy = accuracy_score(y_test_top5, y_pred_top5_tuned) tuned_f1 = f1_score(y_test_top5, y_pred_top5_tuned) # Compute F2 from sklearn.metrics import fbeta_score tuned_f2 = fbeta_score(y_test_top5, y_pred_top5_tuned, beta=2) # Add to summary performance_comparison.loc[len(performance_comparison)] = ["Top-5 Tuned", tuned_accuracy, tuned_f1, tuned_f2

```
print("\nii Final Model Comparison:\n", performance comparison)
     Final Model Comparison:
               Model Accuracy
                                      F1
     0 Top-5 Tuned 0.846224 0.283563 0.222395
#tuned top 5 model
from sklearn.metrics import make_scorer, fbeta_score, accuracy_score, f1_score
from sklearn.model_selection import GridSearchCV
import pandas as pd
# 1. Create performance comparison DataFrame with correct structure
performance_comparison = pd.DataFrame(columns=["Model", "Accuracy", "F1", "F2"])
# 2. Define F2 scoring function
f2_scorer = make_scorer(fbeta_score, beta=2)
# 3. Define hyperparameter grid for Random Forest
param grid = {
    'randomforestclassifier__n_estimators': [50, 100, 200],
    'randomforestclassifier__max_depth': [None, 5, 10]
}
# 4. Create GridSearchCV with pipeline
grid = GridSearchCV(
    simpler_pipeline, # Your pipeline that includes preprocessor + RandomForest
    param_grid,
    scoring=f2_scorer,
    n_jobs=-1,
    verbose=1
)
# 5. Fit the grid search on training data
grid.fit(X_train_top5, y_train_top5)
# 6. Get best model and predictions
best_top5_pipeline = grid.best_estimator_
y_pred_top5_tuned = best_top5_pipeline.predict(X_test_top5)
# 7. Evaluate final tuned model
tuned_accuracy = accuracy_score(y_test_top5, y_pred_top5_tuned)
tuned_f1 = f1_score(y_test_top5, y_pred_top5_tuned)
tuned_f2 = fbeta_score(y_test_top5, y_pred_top5_tuned, beta=2)
# 8. Add to performance comparison table
performance_comparison.loc[len(performance_comparison)] = [
    "Top-5 Tuned (F2)", tuned_accuracy, tuned_f1, tuned_f2
]
# 9. Print results
print("\n ✓ Best Hyperparameters:", grid.best_params_)
print("\nii Final Model Comparison:\n", performance_comparison)
Fitting 5 folds for each of 9 candidates, totalling 45 fits
     ☑ Best Hyperparameters: {'randomforestclassifier__max_depth': None, 'randomforestclassifier__n_estimators': 50}
     Final Model Comparison:
                    Model Accuracy
                                          F1
                                                     F2
     0 Top-5 Tuned (F2) 0.846224 0.283563 0.222395
# plus smote_pipeline
from sklearn.metrics import make_score, fbeta_score, accuracy_score, f1_score
from sklearn.model_selection import GridSearchCV
from imblearn.pipeline import Pipeline # 👈 Use imblearn's Pipeline
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

```
# Define top-5 features (from your feature importance list)
top5_features = ["BMI", "GenHlth", "HighChol", "Age", "HighBP"]
# Identify types
top5_categorical = [col for col in top5_features if X_train_top5[col].dtype == 'object']
top5_numerical = [col for col in top5_features if X_train_top5[col].dtype != 'object']
# Define ColumnTransformer
preprocessor_top5 = ColumnTransformer([
    ("num", StandardScaler(), top5_numerical),
    ("cat", OneHotEncoder(handle_unknown='ignore'), top5_categorical)
])
# 1. Create performance comparison DataFrame
performance_comparison = pd.DataFrame(columns=["Model", "Accuracy", "F1", "F2"])
# 2. Define F2 scoring function
f2_scorer = make_scorer(fbeta_score, beta=2)
# 3. Define hyperparameter grid for Random Forest
param grid = {
    'randomforestclassifier__n_estimators': [50, 100, 200],
    'randomforestclassifier__max_depth': [None, 5, 10]
}
# 🔪 Define the pipeline with SMOTE
smote_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor_top5), # Make sure this is defined before
    ('smote', SMOTE(random_state=42)),
    ('randomforestclassifier', RandomForestClassifier(random_state=42))
1)
# 4. Create GridSearchCV with pipeline
grid = GridSearchCV(
    smote_pipeline,
    param_grid,
    cv=5,
    scoring=f2_scorer,
    n_jobs=-1,
    verbose=1
)
# 5. Fit the grid search on training data
grid.fit(X_train_top5, y_train_top5)
# 6. Get best model and predictions
best_top5_pipeline = grid.best_estimator_
y_pred_top5_tuned = best_top5_pipeline.predict(X_test_top5)
# 7. Evaluate final tuned model
tuned_accuracy = accuracy_score(y_test_top5, y_pred_top5_tuned)
tuned_f1 = f1_score(y_test_top5, y_pred_top5_tuned)
tuned_f2 = fbeta_score(y_test_top5, y_pred_top5_tuned, beta=2)
# 8. Add to performance comparison table
performance_comparison.loc[len(performance_comparison)] = [
    "Top-5 Tuned + SMOTE (F2)", tuned_accuracy, tuned_f1, tuned_f2
1
# 9. Print results
print("\n ✓ Best Hyperparameters:", grid.best params )
print("\n ii Final Model Comparison:\n", performance_comparison)
Fitting 5 folds for each of 9 candidates, totalling 45 fits
     Best Hyperparameters: {'randomforestclassifier_max_depth': 10, 'randomforestclassifier_n_estimators': 50}
     Final Model Comparison:
                            Model Accuracy
     0 Top-5 Tuned + SMOTE (F2) 0.718878 0.463696 0.611488
from sklearn.metrics import make_score, fbeta_score, accuracy_score, f1_score
from sklearn.model_selection import GridSearchCV
from imblearn.pipeline import Pipeline # 👈 Use imblearn's Pipeline
from imblearn.over_sampling import SMOTE
```

```
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
# Define top-5 features (from your feature importance list)
top5_features = ["BMI", "GenHlth", "HighChol", "Age", "HighBP"]
# Identify types
top5_categorical = [col for col in top5_features if X_train_top5[col].dtype == 'object']
top5_numerical = [col for col in top5_features if X_train_top5[col].dtype != 'object']
# Define ColumnTransformer
preprocessor_top5 = ColumnTransformer([
    ("num", StandardScaler(), top5_numerical),
    ("cat", OneHotEncoder(handle unknown='ignore'), top5 categorical)
])
# 1. Create performance comparison DataFrame
performance_comparison = pd.DataFrame(columns=["Model", "Accuracy", "F1", "F2"])
# 2. Define F2 scoring function
f2_scorer = make_scorer(fbeta_score, beta=2)
# 3. Define hyperparameter grid for Random Forest
param_grid = {
    'randomforestclassifier__n_estimators': [50, 100, 200],
    'randomforestclassifier__max_depth': [None, 5, 10]
# % Define the pipeline with SMOTE
smote_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor_top5), # Make sure this is defined before
    ('smote', SMOTE(random_state=42)),
    ('randomforestclassifier', RandomForestClassifier(random_state=42))
])
# 4. Create GridSearchCV with pipeline
grid = GridSearchCV(
    smote_pipeline,
    param_grid,
    cv=5,
    scoring=f2_scorer,
    n_jobs=-1,
    verbose=1
# 5. Fit the grid search on training data
grid.fit(X_train_top5, y_train_top5)
# 6. Get best model and predictions
best_top5_pipeline = grid.best_estimator_
y_pred_top5_tuned = best_top5_pipeline.predict(X_test_top5)
# 7. Evaluate final tuned model
tuned_accuracy = accuracy_score(y_test_top5, y_pred_top5_tuned)
tuned_f1 = f1_score(y_test_top5, y_pred_top5_tuned)
tuned_f2 = fbeta_score(y_test_top5, y_pred_top5_tuned, beta=2)
# 8. Add to performance comparison table
performance comparison.loc[len(performance comparison)] = [
    "Top-5 Tuned + SMOTE (F2)", tuned_accuracy, tuned_f1, tuned_f2
]
# 9. Print results
print("\n ii Final Model Comparison:\n", performance_comparison)
Fitting 5 folds for each of 9 candidates, totalling 45 fits
     ☑ Best Hyperparameters: {'randomforestclassifier__max_depth': 10, 'randomforestclassifier__n_estimators': 50}
     Final Model Comparison:
                           Model Accuracy
                                                  F1
                                                           F2
     0 Top-5 Tuned + SMOTE (F2) 0.718878 0.463696 0.611488
```