Imports

```
# Data Handling
import pandas as pd
import numpy as np

# Preprocessing & Splitting
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

# Machine Learning Models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb

# Model Optimisation (Fine-tuning Hyperparameters)
from sklearn.model_selection import (
    GridSearchCV,
    RandomizedSearchCV,
    StratifiedKFold
)

# Evaluation Metrics
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    classification_report,
    precision_recall_fscore_support,
    confusion_matrix,
    ConfusionMatrixDisplay
)

# Visualisation Tools
import seaborn as sns
import matplotlib.pyplot as plt

# Model Explainer
import shap

# Save/Export Models and Datasets
import pickle
import joblib
from google.colab import files
```

Preprocessing

Loading the Dataset

```
# Load CSVs
features_df = pd.read_csv('datasets/elliptic_txs_features.csv')
classes_df = pd.read_csv('datasets/elliptic_txs_classes.csv')
```

```
Downloading...
From: https://drive.google.com/uc?id=1SO4vme33DCGmL3VTYV9myph9suqlL71s
To: /content/elliptic_txs_classes.csv
100%|██████████| 3.31M/3.31M [00:00<00:00, 184MB/s]
Downloading...
From (original): https://drive.google.com/uc?id=1ZiHg7nmp00qt56xrpOXqB5zor6
From (redirected): https://drive.google.com/uc?id=1ZiHg7nmp00qt56xrpOXqB5zo
To: /content/elliptic_txs_features.csv
100%|██████████| 690M/690M [00:06<00:00, 113MB/s]
```

```
# Quick preview
print("Features shape:", features_df.shape)
display(features_df.head())

print("Classes shape:", classes_df.shape)
display(classes_df.head())
```

```
Features shape: (203768, 167)
```

	230425980	1	-0.1714692896288031	-0.18466755143291433	-1.2013688016765
0	5530458	1	-0.171484	-0.184668	-1.201
1	232022460	1	-0.172107	-0.184668	-1.201
2	232438397	1	0.163054	1.963790	-0.646
3	230460314	1	1.011523	-0.081127	-1.201
4	230459870	1	0.961040	-0.081127	-1.201

5 rows × 167 columns

```
Classes shape: (203769, 2)
```

	txId	class
0	230425980	unknown
1	5530458	unknown
2	232022460	unknown
3	232438397	2
4	230460314	unknown

Cleaning the Dataset

```
# Assign proper names to transaction id and time step features
features_df.rename(columns={features_df.columns[0]: 'txId', features_df.columns

print("Features shape:", features_df.shape)
display(features_df.head())
```

```
Features shape: (203768, 167)
```

	txId	timeStep	-0.1714692896288031	-0.18466755143291433	-1.2013688
0	5530458	1	-0.171484	-0.184668	
1	232022460	1	-0.172107	-0.184668	
2	232438397	1	0.163054	1.963790	
3	230460314	1	1.011523	-0.081127	
4	230459870	1	0.961040	-0.081127	

5 rows × 167 columns

```
# Merge the datasets
transactions_df = pd.merge(features_df, classes_df, on='txId', how='left')

print("Merged data shape:", transactions_df.shape)
transactions_df.head()
```

```
Merged data shape: (203768, 168)
```

	txId	timeStep	-0.1714692896288031	-0.18466755143291433	-1.2013688
0	5530458	1	-0.171484	-0.184668	
1	232022460	1	-0.172107	-0.184668	
2	232438397	1	0.163054	1.963790	
3	230460314	1	1.011523	-0.081127	
4	230459870	1	0.961040	-0.081127	

5 rows × 168 columns

```
# Drop any rows with missing data
transactions_df = transactions_df.dropna()
display(transactions_df)
```

	txId	timeStep	-0.1714692896288031	-0.18466755143291433	-1.20
0	5530458	1	-0.171484	-0.184668	
1	232022460	1	-0.172107	-0.184668	
2	232438397	1	0.163054	1.963790	
3	230460314	1	1.011523	-0.081127	
4	230459870	1	0.961040	-0.081127	
...	...	...	...	...	
203763	173077460	49	-0.145771	-0.163752	
203764	158577750	49	-0.165920	-0.123607	
203765	158375402	49	-0.172014	-0.078182	
203766	158654197	49	-0.172842	-0.176622	
203767	157597225	49	-0.012037	-0.132276	

203768 rows × 168 columns

```
# Find out all the values in class
transactions_df['class'].value_counts()
```

class	count
unknown	157204
2	42019
1	4545

dtype: int64

```
# Drop rows with unknown as the class
no_unknown_df = transactions_df.loc[(transactions_df['class'] != "unknown"), 't
transactions_df = transactions_df.loc[transactions_df['txId'].isin(no_unknown_c

display(transactions_df)
print("Transactions data shape:", transactions_df.shape)
```

	txId	timeStep	-0.1714692896288031	-0.18466755143291433	-1.20
2	232438397	1	0.163054	1.963790	
8	232029206	1	-0.005027	0.578941	
9	232344069	1	-0.147852	-0.184668	
10	27553029	1	-0.151357	-0.184668	
15	3881097	1	-0.172306	-0.184668	
...	...	...	...	...	
203751	80329479	49	-0.159293	-0.037276	
203753	158406298	49	-0.172962	-0.126566	
203758	158375075	49	-0.170412	-0.078164	
203762	147478192	49	-0.093732	-0.116160	
203765	158375402	49	-0.172014	-0.078182	

46564 rows × 168 columns

```
Transactions data shape: (46564, 168)
```

```
# make class only 0s and 1s for binary classification
transactions_df['class'] = transactions_df['class'].replace('2', 0)
transactions_df['class'] = transactions_df['class'].replace('1', 1)
transactions_df['class'].value_counts()
```

```
/tmp/ipython-input-9-1428541033.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
  transactions_df['class'] = transactions_df['class'].replace('2', 0)
/tmp/ipython-input-9-1428541033.py:3: FutureWarning: Downcasting behavior i
  transactions_df['class'] = transactions_df['class'].replace('1', 1)
/tmp/ipython-input-9-1428541033.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
  transactions_df['class'] = transactions_df['class'].replace('1', 1)
```

class	count
0	42019
1	4545

dtype: int64

Splitting the Data into Train/Test Sets

```
# Split the features from the target and remove redundant features
X_raw = transactions_df.drop(columns=['txId', 'timeStep', 'class'])
y_raw = transactions_df['class']

print("X shape:", X_raw.shape)
print("y shape:", y_raw.shape)
```

```
X shape: (46564, 165)
y shape: (46564,)
```

```
# Split the data into 70% training, 30% testing
X_train_raw, X_test_raw, y_train, y_test = train_test_split(X_raw, y_raw, test_

display(X_train_raw.head())
print(f"Train set: {X_train_raw.shape}")
display(X_test_raw.head())
print(f"Test set: {X_test_raw.shape}")
```

	-0.1714692896288031	-0.18466755143291433	-1.2013688016765636	-0.1
147393	-0.147861	-0.016933	-0.091383	
33575	-0.159984	-0.184668	-1.201369	
103549	-0.167092	-0.158783	-1.201369	
130185	-0.172687	-0.024186	1.018602	
42840	-0.172408	-0.081127	-1.201369	

5 rows × 165 columns

```
Train set: (32594, 165)
```

	-0.1714692896288031	-0.18466755143291433	-1.2013688016765636	-0.1
42795	-0.172924	0.031421	0.463609	
182513	-0.058037	-0.113846	0.463609	
186795	-0.172945	-0.123312	1.018602	
32051	-0.156359	-0.184668	-1.201369	
86105	-0.172951	-0.175452	0.463609	

5 rows × 165 columns

```
Test set: (13970, 165)
```

Scaling Numerical Features

```
# Scale the numerical features using MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(X_train_raw)
X_train = scaler.transform(X_train_raw)
X_test = scaler.transform(X_test_raw)
```

Initial Model Training and Evaluation

```
def evaluate_model(model, model_name="Model"):
    # Predict on train and test
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    # Calculate metrics
    accuracy_train = accuracy_score(y_train, y_pred_train)
    accuracy_test = accuracy_score(y_test, y_pred_test)

    precision_train = precision_score(y_train, y_pred_train)
    precision_test = precision_score(y_test, y_pred_test)

    recall_train = recall_score(y_train, y_pred_train)
    recall_test = recall_score(y_test, y_pred_test)

    f1_train = f1_score(y_train, y_pred_train)
    f1_test = f1_score(y_test, y_pred_test)

    # Prepare results DataFrame
    results_df = pd.DataFrame([
        ['Accuracy', accuracy_train, accuracy_test],
        ['Precision', precision_train, precision_test],
        ['Recall', recall_train, recall_test],
        ['F1 Score', f1_train, f1_test]
    ], columns=['Metric', 'Train', 'Test'])

    print(f"{model_name} Results:")
    display(results_df)

    # Return metrics and predictions
    return results_df, y_pred_train, y_pred_test
```

Logistic Regression

```
lr_model = LogisticRegression(max_iter=1000, random_state=0)
lr_model.fit(X_train, y_train)

results_lr, y_pred_train_lr, y_pred_test_lr = evaluate_model(lr_model, model_na
```

```
Logistic Regression Results:
```

	Metric	Train	Test
0	Accuracy	0.917408	0.917323
1	Precision	0.689977	0.689655
2	Recall	0.279157	0.278592
3	F1 Score	0.397493	0.396867

Random Forest

```
rf_model = RandomForestClassifier(random_state=0)
rf_model.fit(X_train, y_train)

results_rf, y_pred_train_rf, y_pred_test_rf = evaluate_model(rf_model, model_na
```

```
Random Forest Results:
```

	Metric	Train	Test
0	Accuracy	1.0	0.987688
1	Precision	1.0	0.994196
2	Recall	1.0	0.879032
3	F1 Score	1.0	0.933074

XGBClassifier

```
xgb_model = xgb.XGBClassifier(eval_metric='logloss', random_state=0)
xgb_model.fit(X_train, y_train)
results_xgb, y_pred_train_xgb, y_pred_test_xgb= evaluate_model(xgb_model, model
```

```
XGBClassifier Results:
```

	Metric	Train	Test
0	Accuracy	1.0	0.991410
1	Precision	1.0	0.984424
2	Recall	1.0	0.926686
3	F1 Score	1.0	0.954683

Storing Results For Later Comparison

```
before_optimisation_results = {
    'Logistic Regression': results_lr,
    'Random Forest': results_rf,
    'XGBClassifier': results_xgb
}
```

Model Optimisation (Fine-tuning Hyperparameters)

Grid Search

```
def finetune_model_using_gridsearch(model, param_grid, X_train, y_train, scorir
    if model_name:
        print(f"\nTuning hyperparameters for {model_name}...\n")

    grid_search = GridSearchCV(
        estimator=model,
        param_grid=param_grid,
        scoring=scoring,
        cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=0),
        verbose=1,
        n_jobs=-1
    )

    grid_search.fit(X_train, y_train)

    print(f"\nBest parameters for {model_name}:\n{grid_search.best_params_}")
    print(f"Best {scoring} score: {grid_search.best_score_:.4f}\n")

    return grid_search.best_estimator_, grid_search
```

Randomised Search

```
def finetune_model_using_randomisedsearch(model, param_grid, X_train, y_train,
    if model_name:
        print(f"\nTuning hyperparameters for {model_name}...\n")

    grid_search = RandomizedSearchCV(
        estimator=model,
        param_distributions=param_grid,
        n_iter=5,
        scoring=scoring,
        cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=0),
        verbose=1,
        n_jobs=-1,
        random_state=0
    )

    grid_search.fit(X_train, y_train)

    print(f"\nBest parameters for {model_name}:\n{grid_search.best_params_}")
    print(f"Best {scoring} score: {grid_search.best_score_:.4f}\n")

    return grid_search.best_estimator_, grid_search
```

Logistic Regression

```
# Defines parameter grid
param_grid_lr = {
    'tol': [1e-5, 1e-4, 1e-3, 1e-2],
    'solver': ['liblinear'],
    'C': [0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'max_iter': [50, 100, 300]
}

# Fine-tunes model
lr_best_model, lr_grid = finetune_model_using_randomisedsearch(
    LogisticRegression(max_iter=1000, random_state=0),
    param_grid_lr,
    X_train,
    y_train,
    model_name="Logistic Regression"
)
```

```
Tuning hyperparameters for Logistic Regression...

Fitting 4 folds for each of 5 candidates, totalling 20 fits

Best parameters for Logistic Regression:
{'tol': 1e-05, 'solver': 'liblinear', 'penalty': 'l1', 'max_iter': 50, 'C':
Best f1 score: 0.8039

/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: Converge
  warnings.warn(
```

Random Forest

```
# Defines parameter grid
param_grid_rf = {
    'n_estimators': [100, 200, 500],
    'max_depth': [10, 20, 50, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', None],
    'class_weight': ['balanced', None]
}

# Fine-tunes model
rf_best_model, rf_grid = finetune_model_using_randomisedsearch(
    model=RandomForestClassifier(random_state=0),
    param_grid=param_grid_rf,
    X_train=X_train,
    y_train=y_train,
    model_name="Random Forest"
)
```

```
Tuning hyperparameters for Random Forest...

Fitting 4 folds for each of 5 candidates, totalling 20 fits

Best parameters for Random Forest:
{'n_estimators': 500, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_
Best f1 score: 0.9306
```

XGBClassifier

```
# Defines parameter grid
param_grid_xgb = {
    'n_estimators': [100, 300, 500],
    'max_depth': [3, 6, 10],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0],
    'gamma': [0, 1, 5],
    'reg_alpha': [0, 0.1, 1],
    'reg_lambda': [0.1, 1, 10],
    'scale_pos_weight': [1, 10, 20]
}

# Fine-tunes model
xgb_best_model, xgb_grid = finetune_model_using_randomisedsearch(
    xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_st
    param_grid_xgb,
    X_train,
    y_train,
    model_name="XGBClassifier"
)
```

```
Tuning hyperparameters for XGBClassifier...

Fitting 4 folds for each of 5 candidates, totalling 20 fits
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarnin
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)

Best parameters for XGBClassifier:
{'subsample': 1.0, 'scale_pos_weight': 20, 'reg_lambda': 1, 'reg_alpha': 0.
Best f1 score: 0.9500
```

Re-training models using optimal parameters

```
results_lr, y_pred_train_lr, y_pred_test_lr = evaluate_model(lr_best_model, "Lo
```

```
Logistic Regression (Optimised) Results:
```

	Metric	Train	Test
0	Accuracy	0.965638	0.963064
1	Precision	0.854245	0.830218
2	Recall	0.781201	0.781525
3	F1 Score	0.816092	0.805136

```
results_rf, y_pred_train_rf, y_pred_test_rf = evaluate_model(rf_best_model, "Ra
```

```
Random Forest (Optimised) Results:
```

	Metric	Train	Test
0	Accuracy	0.996472	0.987115
1	Precision	0.999023	0.983660
2	Recall	0.964791	0.882698
3	F1 Score	0.981609	0.930448

```
results_xgb, y_pred_train_xgb, y_pred_test_xgb = evaluate_model(xgb_best_model,
```

```
XGBClassifier (Optimised) Results:
```

	Metric	Train	Test
0	Accuracy	0.999540	0.991696
1	Precision	0.995307	0.960857
2	Recall	1.000000	0.953812
3	F1 Score	0.997648	0.957322

```
# Storing Results For Later Comparison
after_optimisation_results = {
    'Logistic Regression': results_lr,
    'Random Forest': results_rf,
    'XGBClassifier': results_xgb
}
```

Performance Results and Comparison

Performance Before vs After Model Optimisation

```
def compile_split_comparison_tables(before_results, after_results, model_name):
    metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

    train_before = before_results[model_name]['Train'].values
    train_after = after_results[model_name]['Train'].values
    train_delta = train_after - train_before

    test_before = before_results[model_name]['Test'].values
    test_after = after_results[model_name]['Test'].values
    test_delta = test_after - test_before

    train_df = pd.DataFrame({
        'Metric': metrics,
        'Train (Before)': train_before,
        'Train (After)': train_after,
        'Train Δ': train_delta
    })

    test_df = pd.DataFrame({
        'Metric': metrics,
        'Test (Before)': test_before,
        'Test (After)': test_after,
        'Test Δ': test_delta
    })

    return train_df, test_df

for model_name in before_optimisation_results.keys():
    print(f"\nTrain Comparison for {model_name}")
    train_table, test_table = compile_split_comparison_tables(before_optimisati
    display(train_table)

    print(f"\nTest Comparison for {model_name}")
    display(test_table)
```

```
Train Comparison for Logistic Regression
```

	Metric	Train (Before)	Train (After)	Train Δ
0	Accuracy	0.917408	0.965638	0.048230

1	Precision	0.689977	0.854245	0.164269
2	Recall	0.279157	0.781201	0.502043
3	F1 Score	0.397493	0.816092	0.418599

Test Comparison for Logistic Regression

	Metric	Test (Before)	Test (After)	Test Δ
0	Accuracy	0.917323	0.963064	0.045741
1	Precision	0.689655	0.830218	0.140563
2	Recall	0.278592	0.781525	0.502933
3	F1 Score	0.396867	0.805136	0.408269

Train Comparison for Random Forest

	Metric	Train (Before)	Train (After)	Train Δ
0	Accuracy	1.0	0.996472	-0.003528
1	Precision	1.0	0.999023	-0.000977
2	Recall	1.0	0.964791	-0.035209
3	F1 Score	1.0	0.981609	-0.018391

Test Comparison for Random Forest

	Metric	Test (Before)	Test (After)	Test Δ
0	Accuracy	0.987688	0.987115	-0.000573
1	Precision	0.994196	0.983660	-0.010536
2	Recall	0.879032	0.882698	0.003666
3	F1 Score	0.933074	0.930448	-0.002626

Train Comparison for XGBClassifier

	Metric	Train (Before)	Train (After)	Train Δ
0	Accuracy	1.0	0.999540	-0.000460
1	Precision	1.0	0.995307	-0.004693
2	Recall	1.0	1.000000	0.000000
3	F1 Score	1.0	0.997648	-0.002352

Test Comparison for XGBClassifier

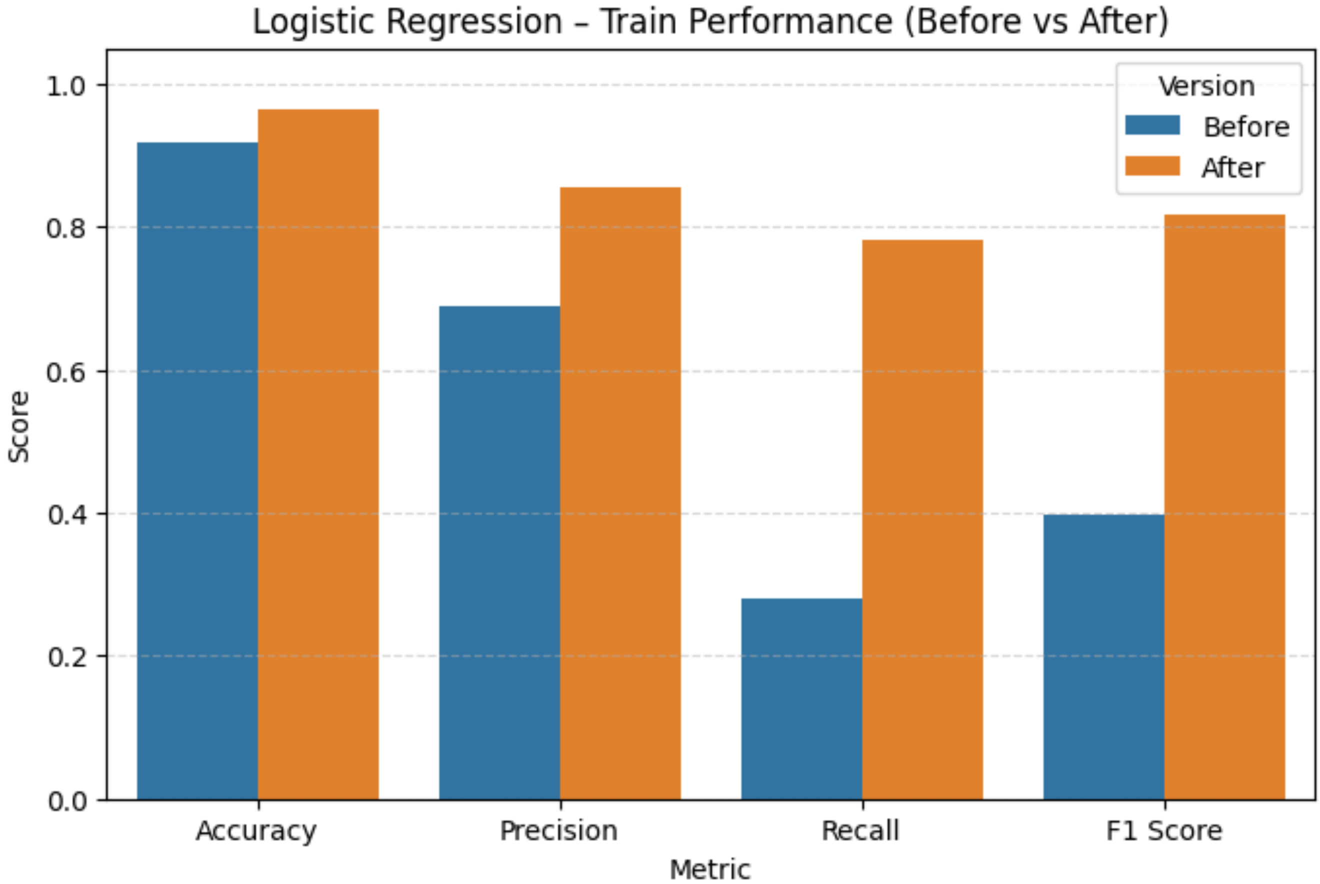
	Metric	Test (Before)	Test (After)	Test Δ

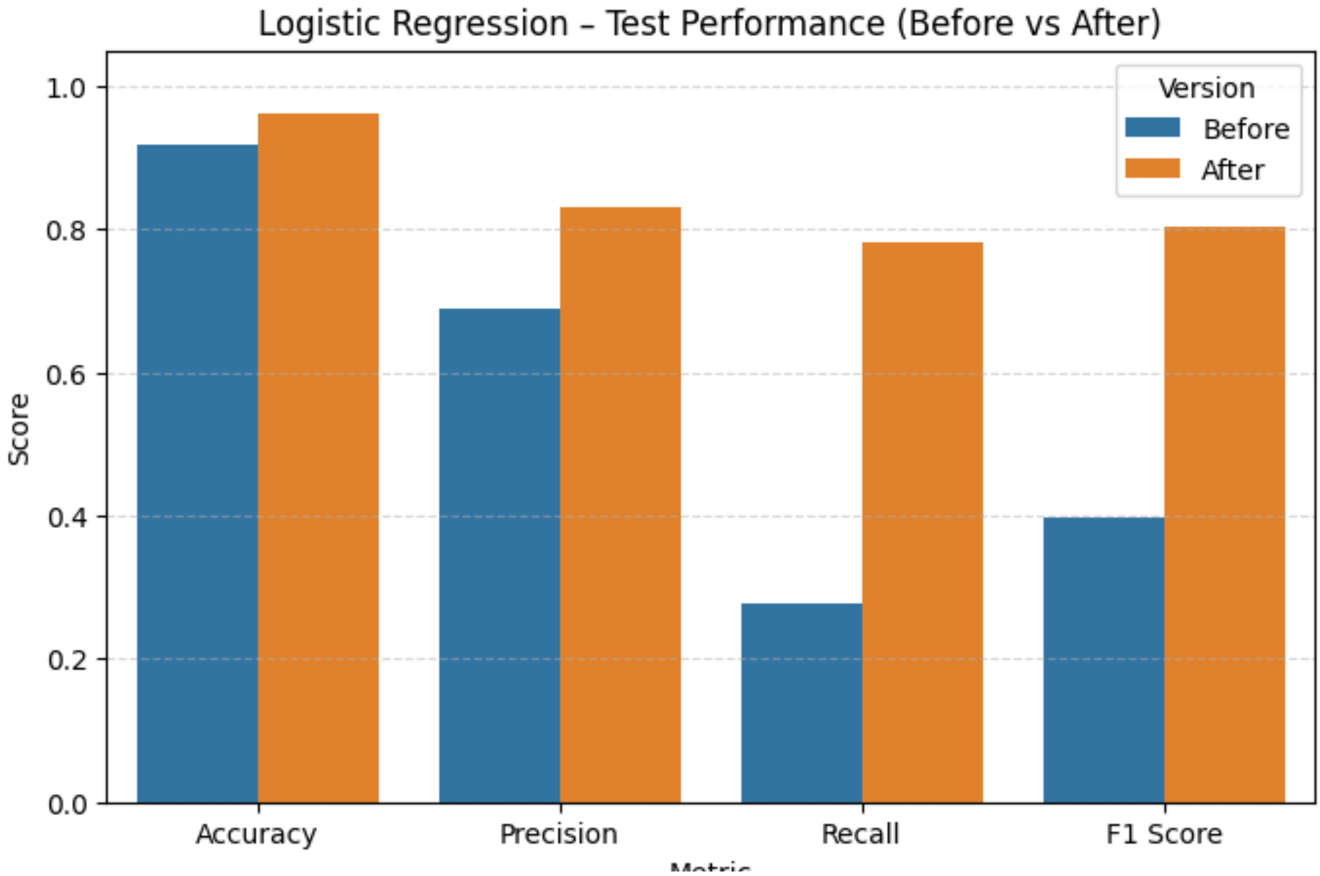
0	Accuracy	0.991410	0.991696	0.000286
1	Precision	0.984424	0.960857	-0.023567
2	Recall	0.926686	0.953812	0.027126
3	F1 Score	0.954683	0.957322	0.002639

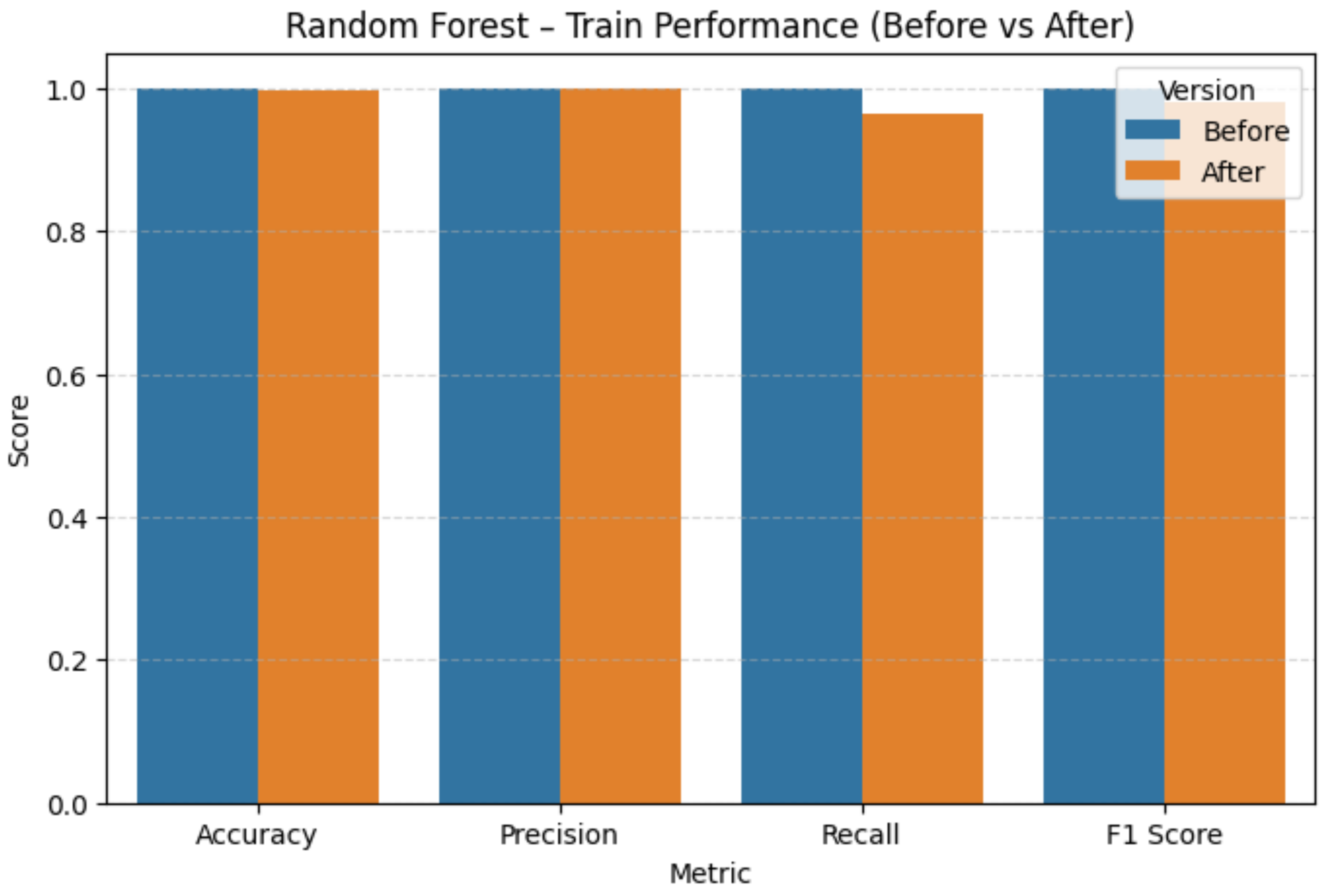
Next steps: Generate code with `train_table` View recommended plots New interactive sheet

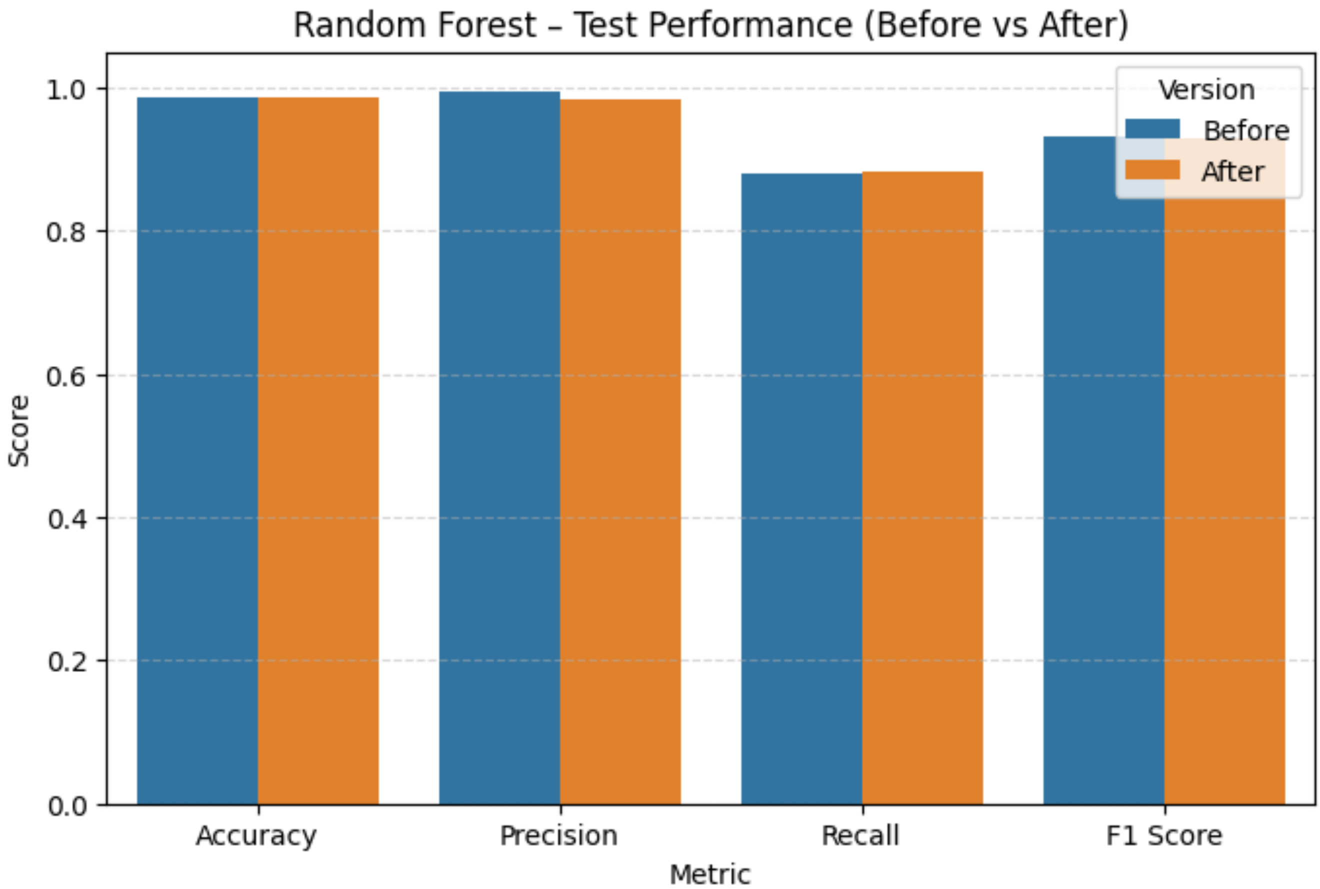
```
def plot_model_before_after_bars(model_name, before_results, after_results):
    metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

    # Extract values
    train_before = before_results[model_name]['Train'].values
    train_after = after_results[model_name]['Train'].values
    test_before = before_results[model_name]['Test'].values
    test_after = after_results[model_name]['Test'].values

    # Prepare data for plotting
    train_data = pd.DataFrame({
        'Metric': metrics,
        'Before': train_before,
        'After': train_after
    }).melt(id_vars='Metric', var_name='Version', value_name='Score')

    test_data = pd.DataFrame({
        'Metric': metrics,
        'Before': test_before,
        'After': test_after
    }).melt(id_vars='Metric', var_name='Version', value_name='Score')

    # Plot Train
    plt.figure(figsize=(8, 5))
    sns.barplot(data=train_data, x='Metric', y='Score', hue='Version')
    plt.title(f'{model_name} – Train Performance (Before vs After)')
    plt.ylim(0, 1.05)
    plt.grid(axis='y', linestyle='--', alpha=0.5)
    plt.show()

    # Plot Test
    plt.figure(figsize=(8, 5))
    sns.barplot(data=test_data, x='Metric', y='Score', hue='Version')
    plt.title(f'{model_name} – Test Performance (Before vs After)')
    plt.ylim(0, 1.05)
    plt.grid(axis='y', linestyle='--', alpha=0.5)
    plt.show()
```

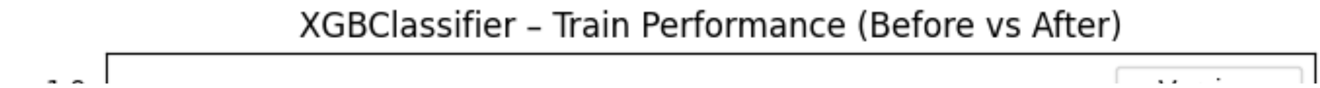
```
for model_name in before_optimisation_results.keys():
    plot_model_before_after_bars(model_name, before_optimisation_results, after
```

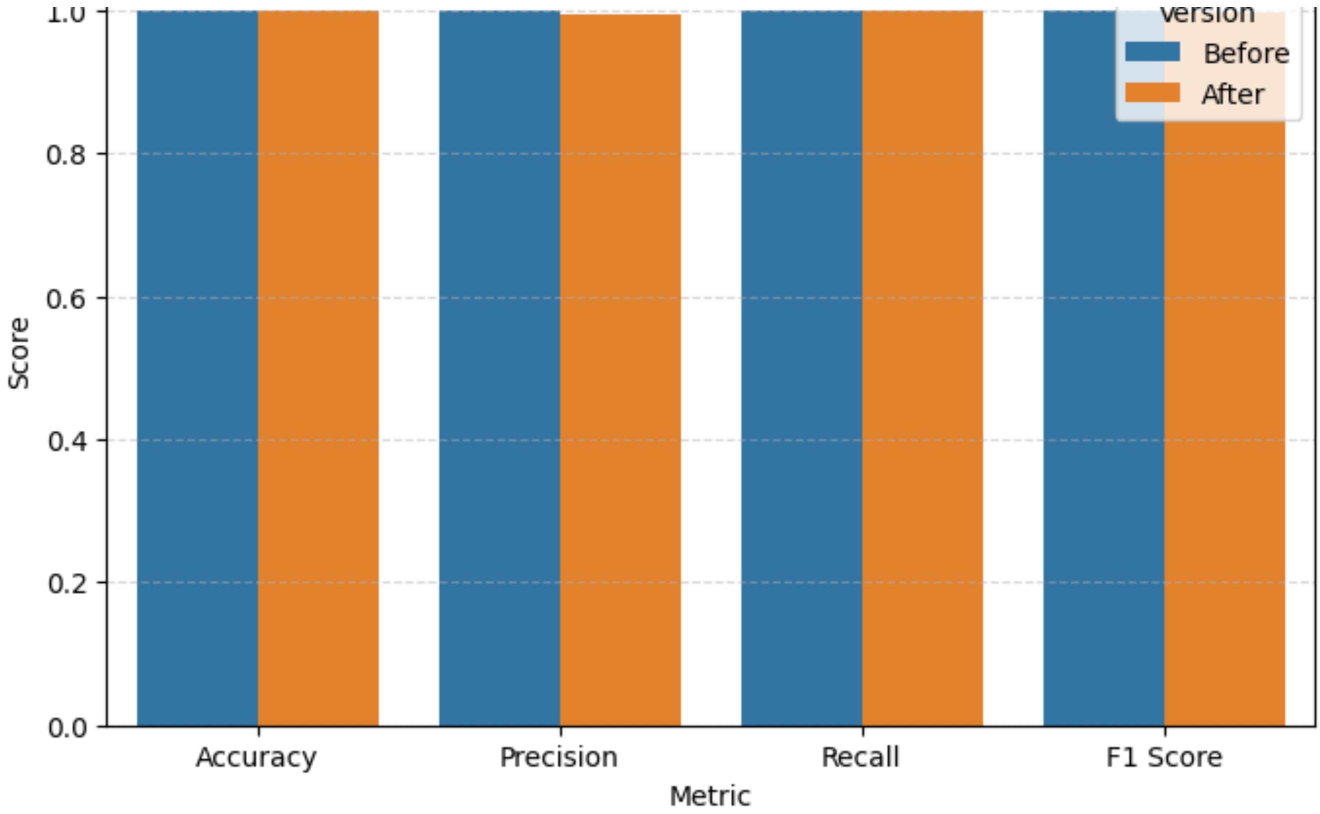


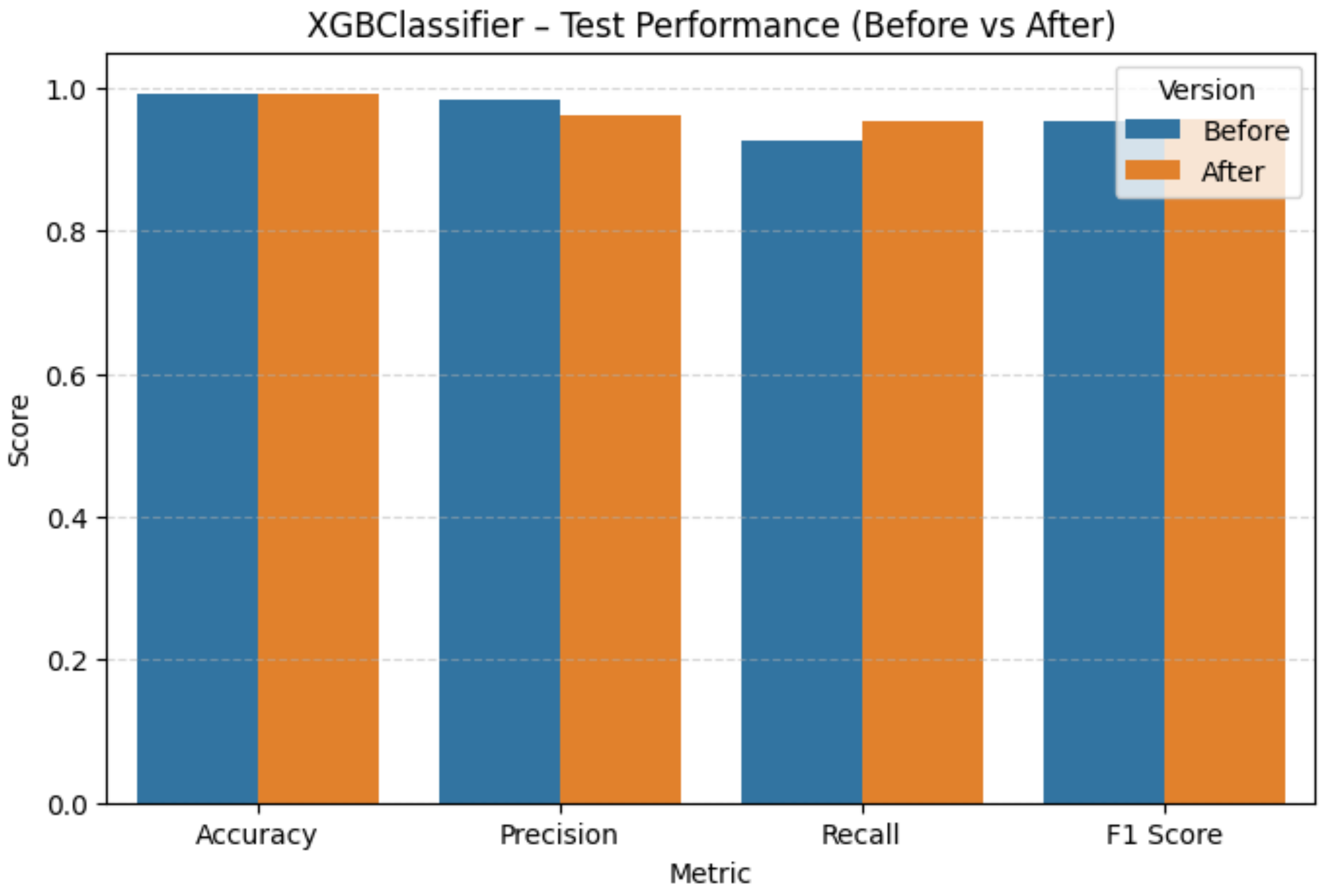



Random Forest – Train Performance (Before vs After)
Version
Before
After
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
Metric


Random Forest – Test Performance (Before vs After)
Version
Before
After
1.0
0.8
0.6
0.4
0.2
0.0
Score
Accuracy
Precision
Recall
F1 Score
Metric


XGBClassifier – Train Performance (Before vs After)


Version
Before
After
Score
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Precision
Recall
F1 Score
Metric


XGBClassifier – Test Performance (Before vs After)
Version
Before
After
Score
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Precision
Recall
F1 Score
Metric

Comparing Performance Between Models

```
def create_metric_table(metric_name, model_results_dict):
    rows = []

    for model_name, df in model_results_dict.items():
        # Extract train and test values for the given metric
        metric_row = df[df['Metric'] == metric_name]
        if not metric_row.empty:
            train_val = metric_row['Train'].values[0]
            test_val = metric_row['Test'].values[0]
            rows.append([model_name, train_val, test_val])

    # Create DataFrame and sort by Test performance
    df_metric = pd.DataFrame(rows, columns=['Model', 'Train', 'Test'])
    df_metric_sorted = df_metric.sort_values(by='Test', ascending=False).reset_

    return df_metric_sorted

# Show sorted comparison tables for each metric
for metric in ['Accuracy', 'Precision', 'Recall', 'F1 Score']:
    print(f"\n{metric} Comparison")
    display(create_metric_table(metric, after_optimisation_results))
```

Accuracy Comparison

	Model	Train	Test
0	XGBClassifier	0.999540	0.991696
1	Random Forest	0.996472	0.987115
2	Logistic Regression	0.965638	0.963064

Precision Comparison

	Model	Train	Test
0	Random Forest	0.999023	0.983660
1	XGBClassifier	0.995307	0.960857
2	Logistic Regression	0.854245	0.830218

Recall Comparison

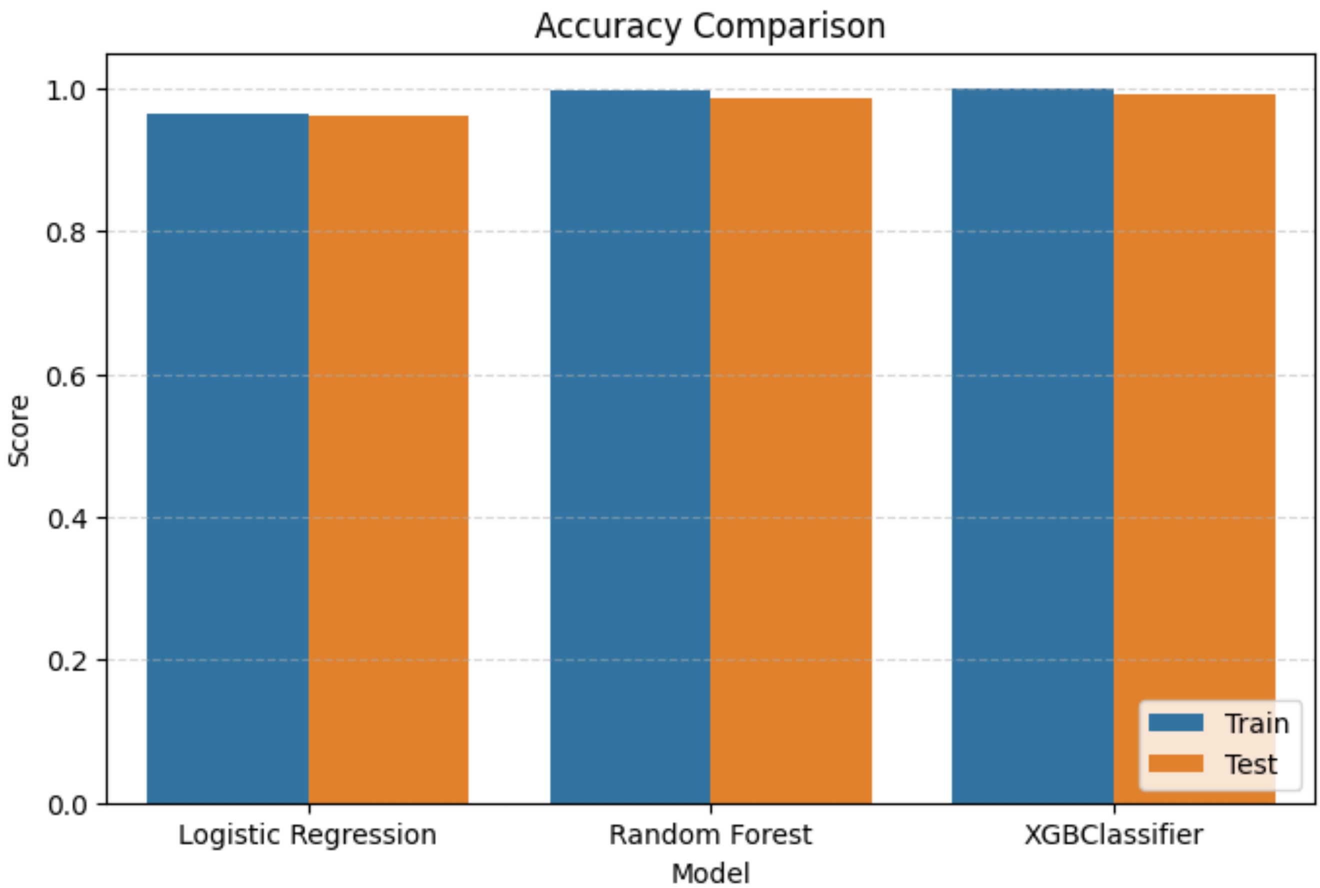
	Model	Train	Test
0	XGBClassifier	1.000000	0.953812
1	Random Forest	0.964791	0.882698
2	Logistic Regression	0.781201	0.781525

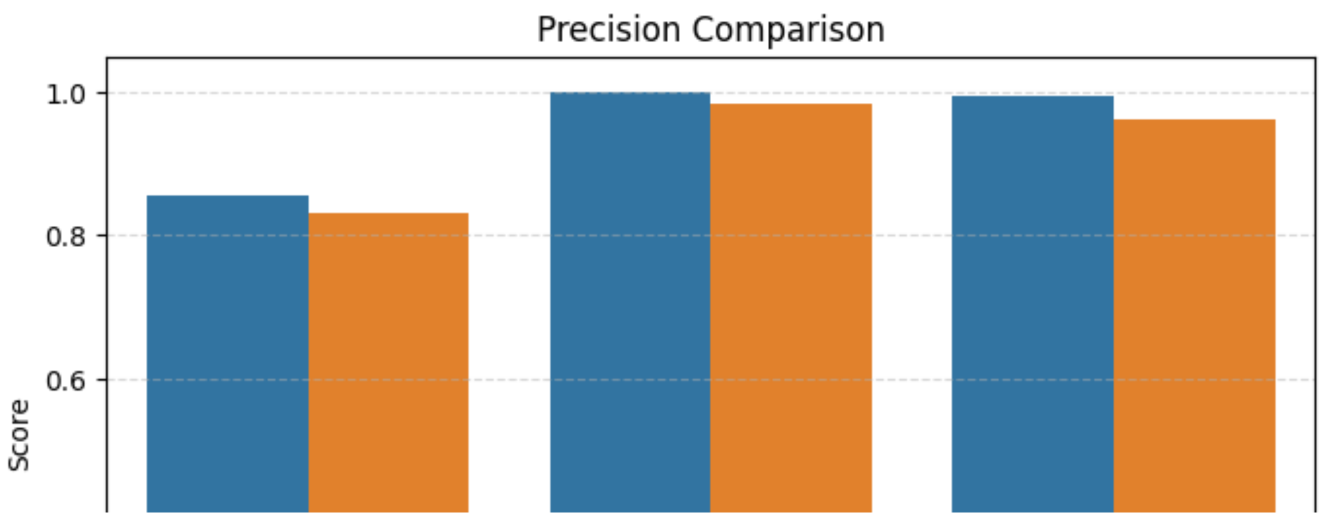
F1 Score Comparison

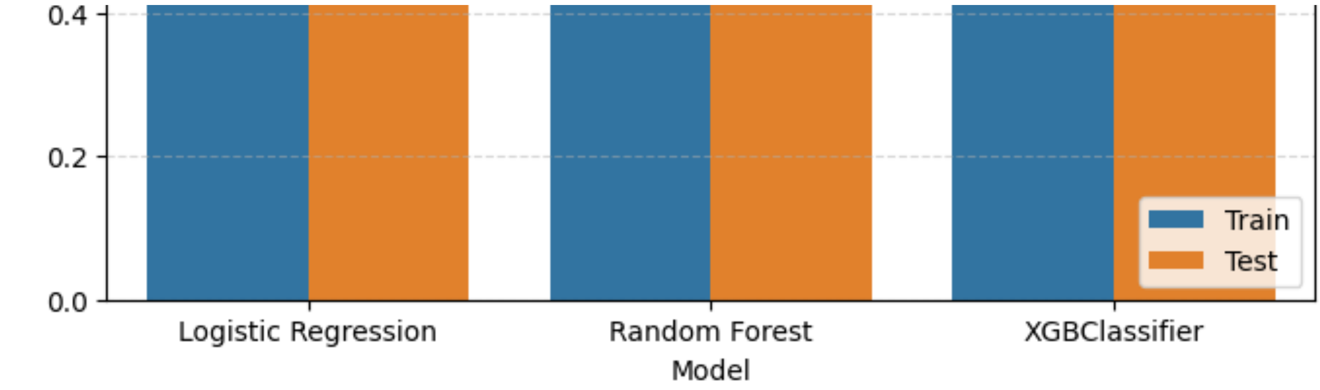
	Model	Train	Test
0	XGBClassifier	0.997648	0.957322
1	Random Forest	0.981609	0.930448
2	Logistic Regression	0.816092	0.805136

```
def plot_metric_bar_chart(metric_name, model_results_dict):

    data = []

    for model_name, df in model_results_dict.items():
        row = df[df['Metric'] == metric_name]
        if not row.empty:
            train_val = row['Train'].values[0]
            test_val = row['Test'].values[0]
            data.append({'Model': model_name, 'Set': 'Train', 'Score': train_va
            data.append({'Model': model_name, 'Set': 'Test', 'Score': test_val}
```

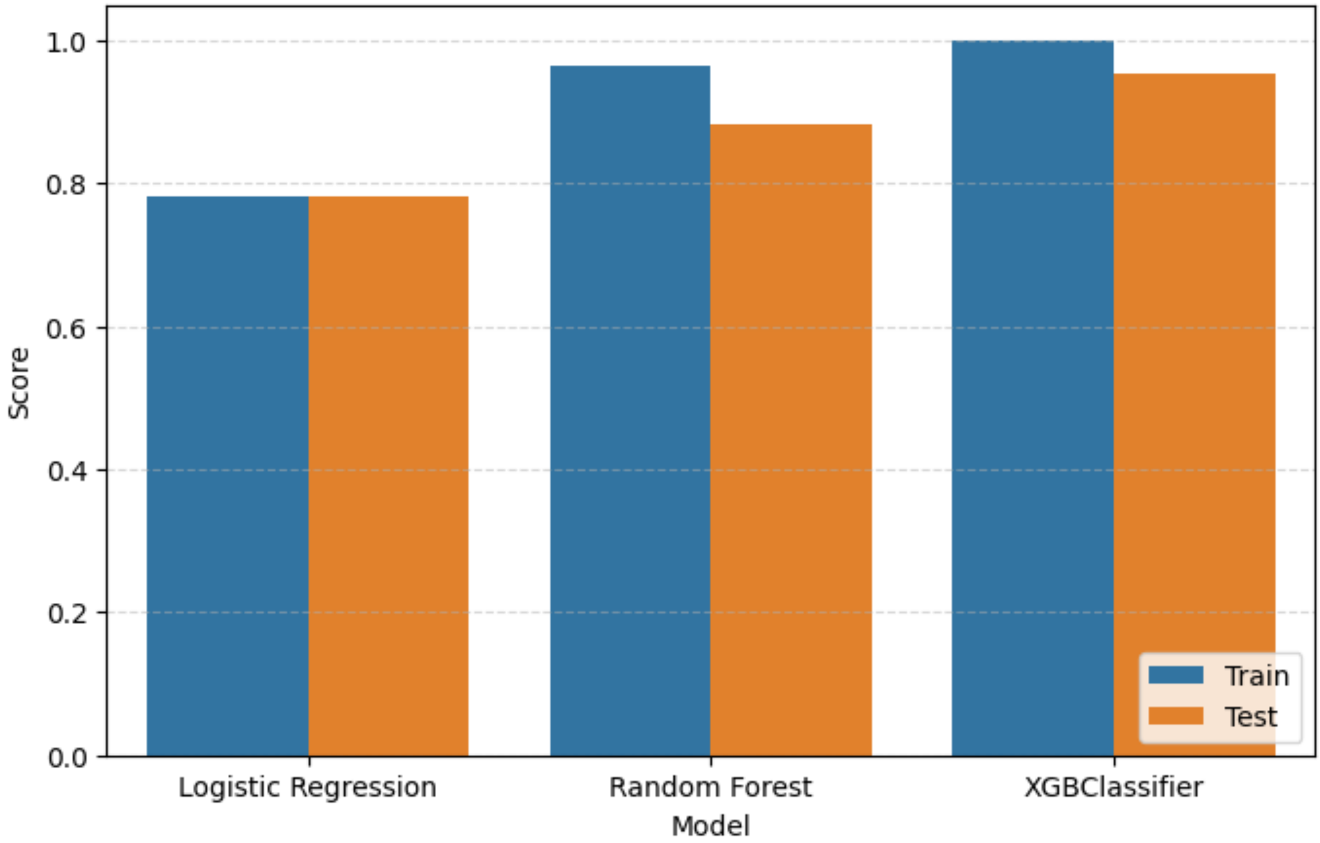
```
    df_plot = pd.DataFrame(data)

    plt.figure(figsize=(8, 5))
    sns.barplot(data=df_plot, x='Model', y='Score', hue='Set')
    plt.title(f'{metric_name} Comparison')
    plt.ylim(0, 1.05)
    plt.legend(loc='lower right')
    plt.grid(axis='y', linestyle='--', alpha=0.5)
    plt.show()

for metric in ['Accuracy', 'Precision', 'Recall', 'F1 Score']:
    plot_metric_bar_chart(metric, after_optimisation_results)
```



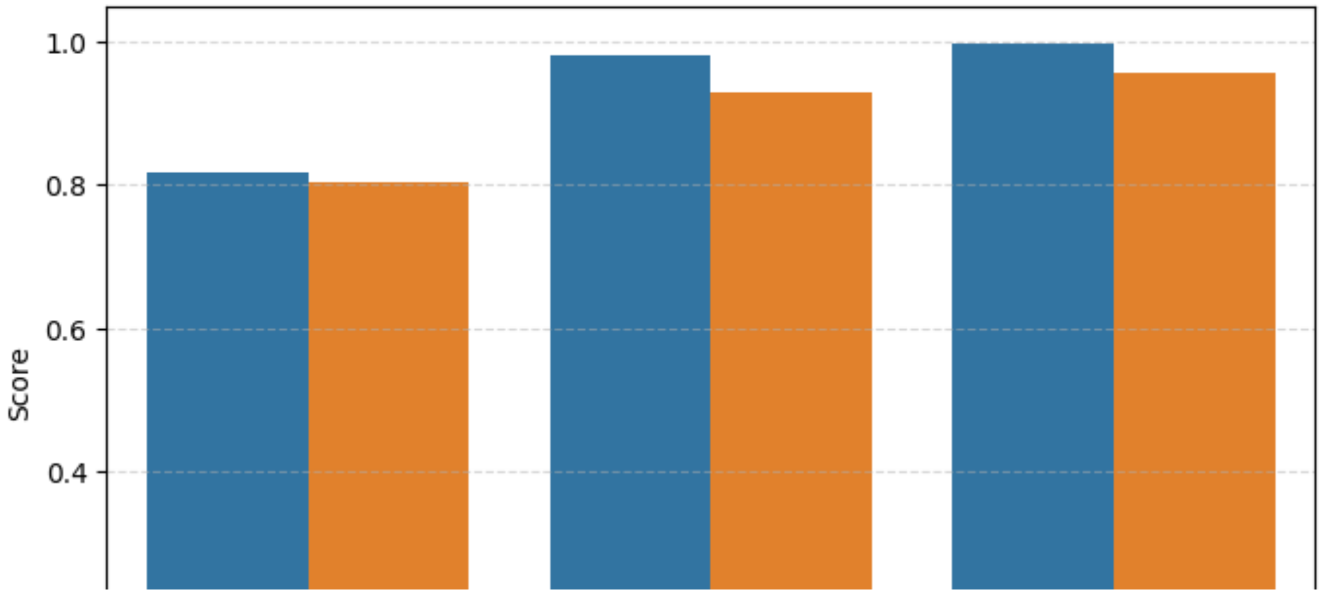


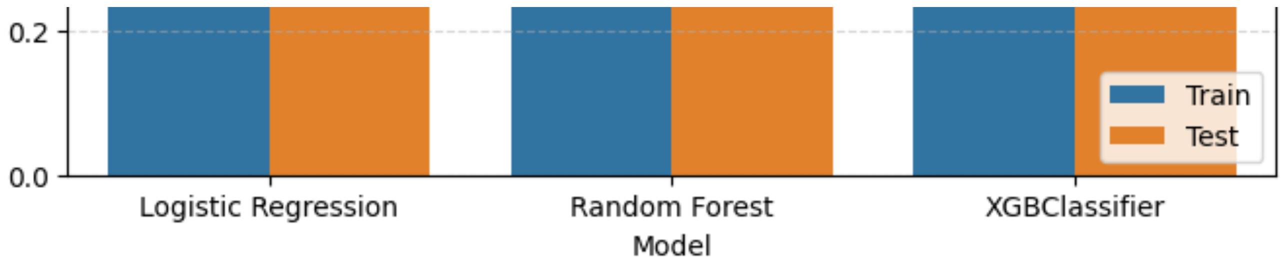


Recall Comparison



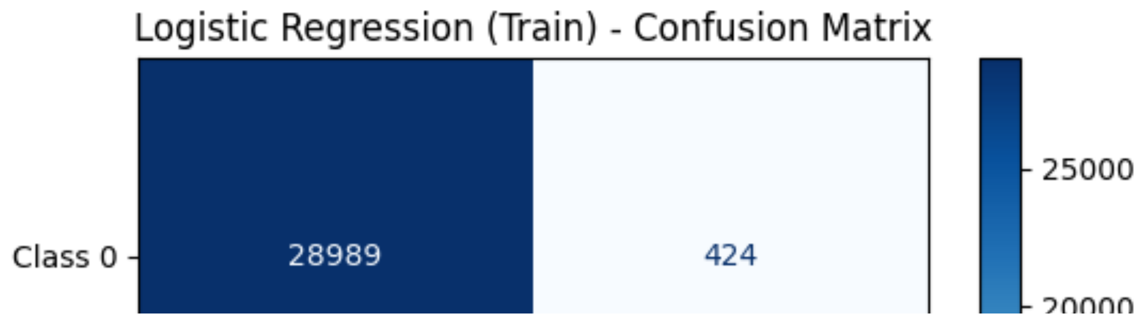
F1 Score Comparison

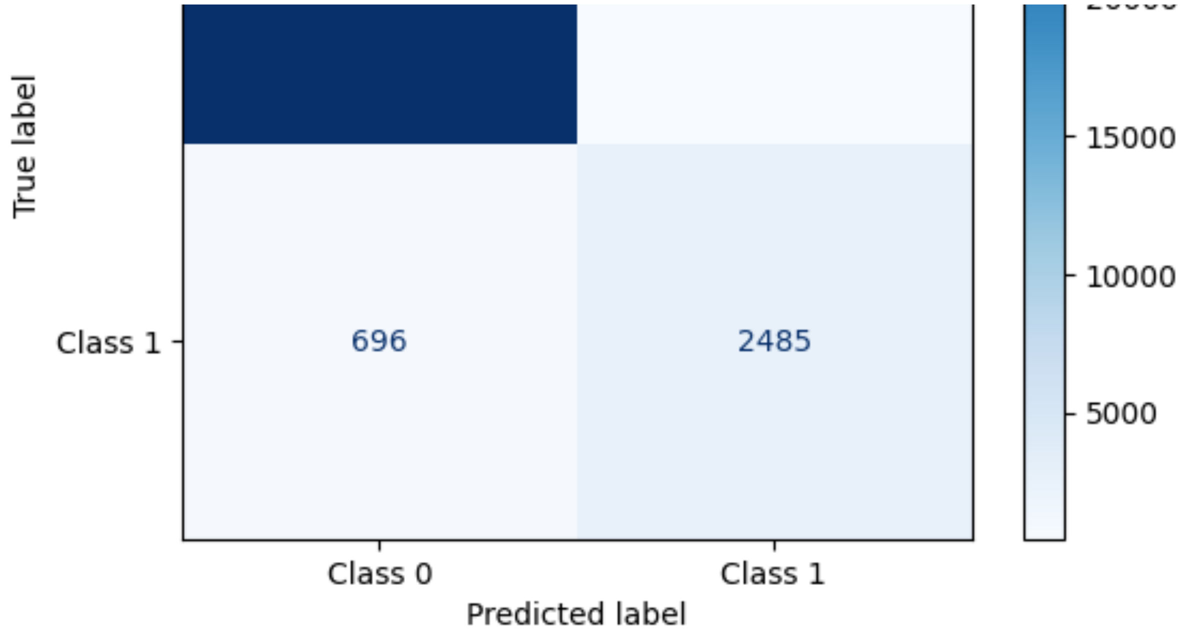




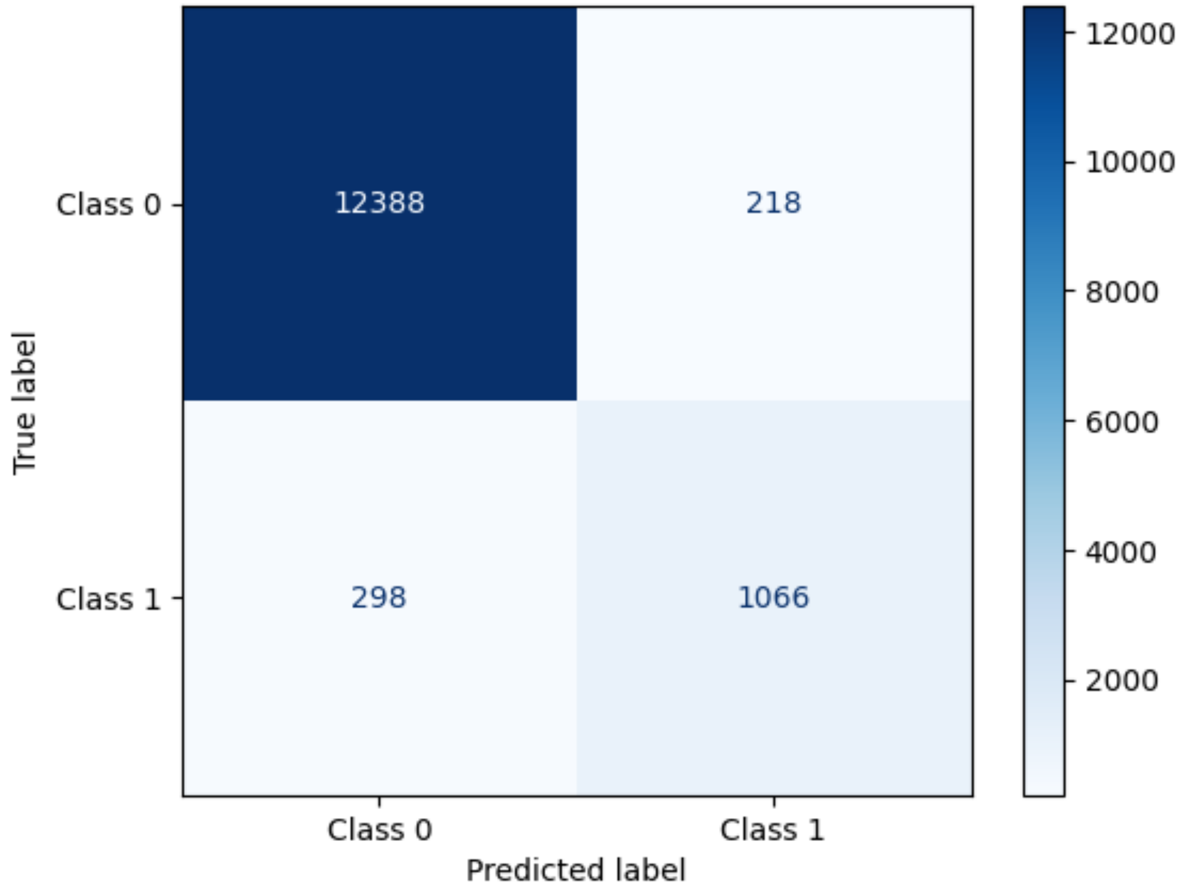
Confusion Matrix For Each Model

```
def plot_confusion_matrix(y_true, y_pred, model_name):
    disp = ConfusionMatrixDisplay.from_predictions(
        y_true, y_pred,
        display_labels=["Class 0", "Class 1"],
        cmap='Blues',
        normalize=None
    )
    disp.ax_.set_title(f'{model_name} - Confusion Matrix')
    plt.show()


plot_confusion_matrix(y_train, y_pred_train_lr, "Logistic Regression (Train)")
plot_confusion_matrix(y_test, y_pred_test_lr, "Logistic Regression (Test)")

plot_confusion_matrix(y_train, y_pred_train_rf, "Random Forest (Train)")
plot_confusion_matrix(y_test, y_pred_test_rf, "Random Forest  (Test)")

plot_confusion_matrix(y_train, y_pred_train_xgb, "XGBClassifier (Train)")
plot_confusion_matrix(y_test, y_pred_test_xgb, "XGBClassifier (Test)")
```

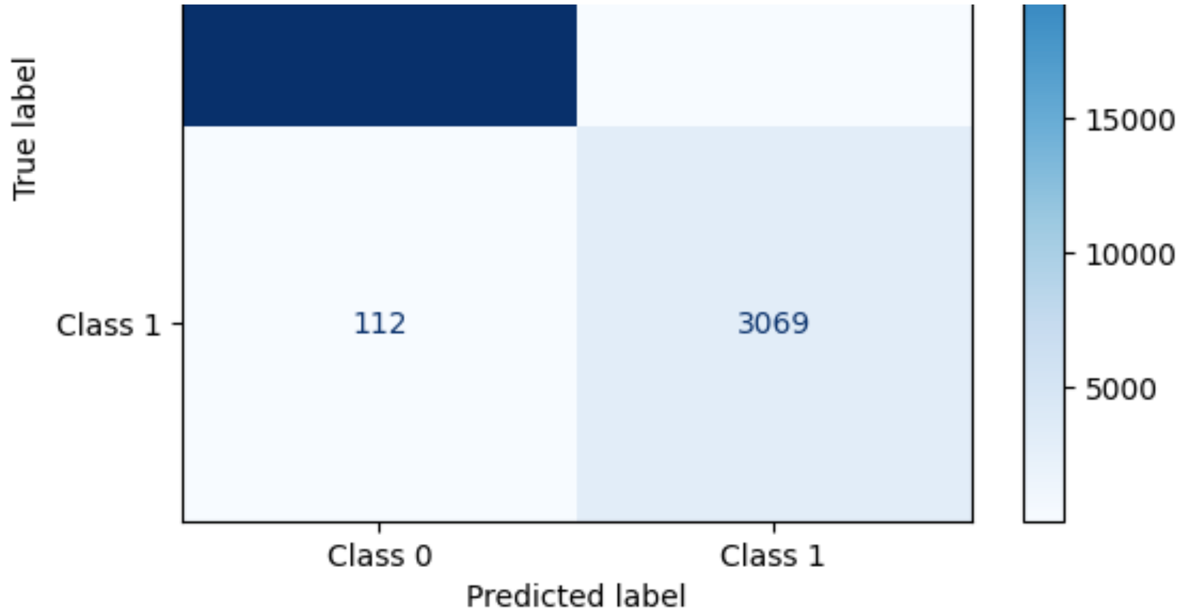




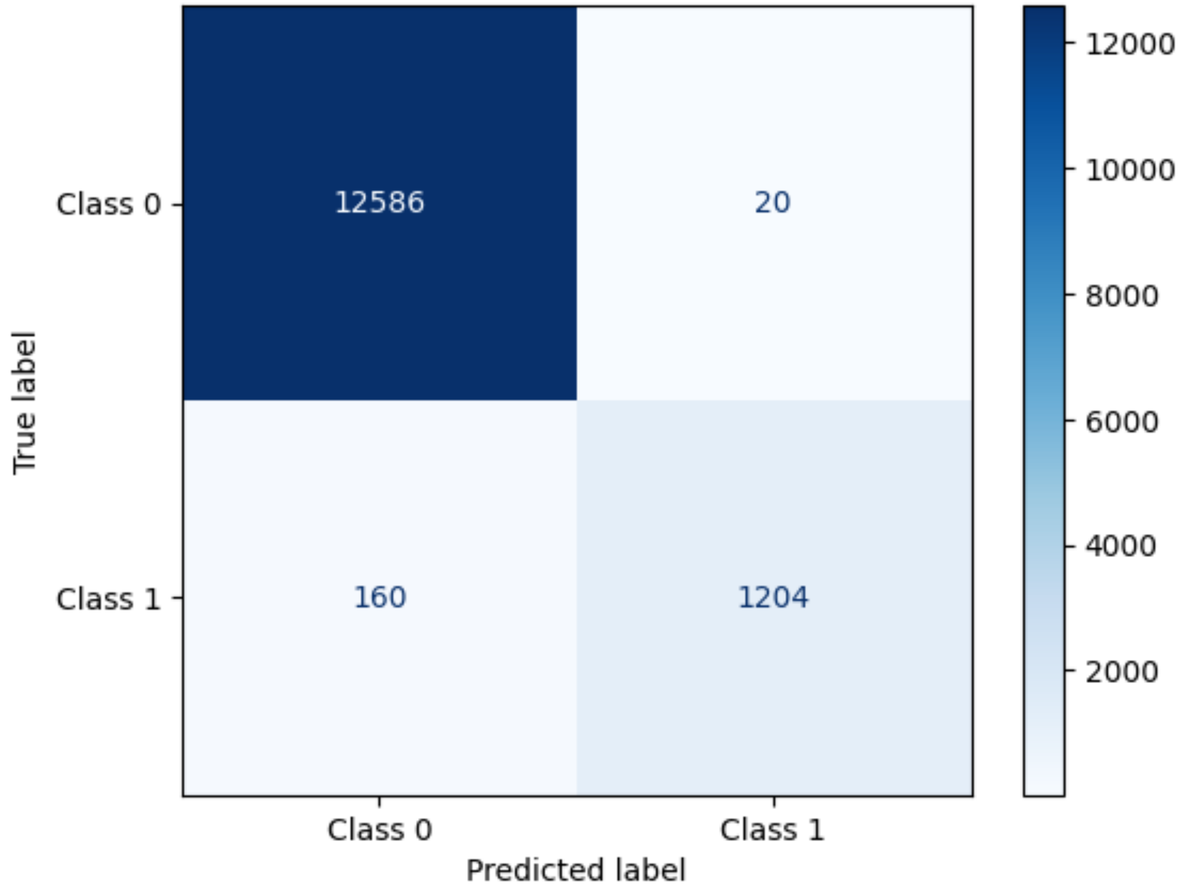
Logistic Regression (Test) - Confusion Matrix



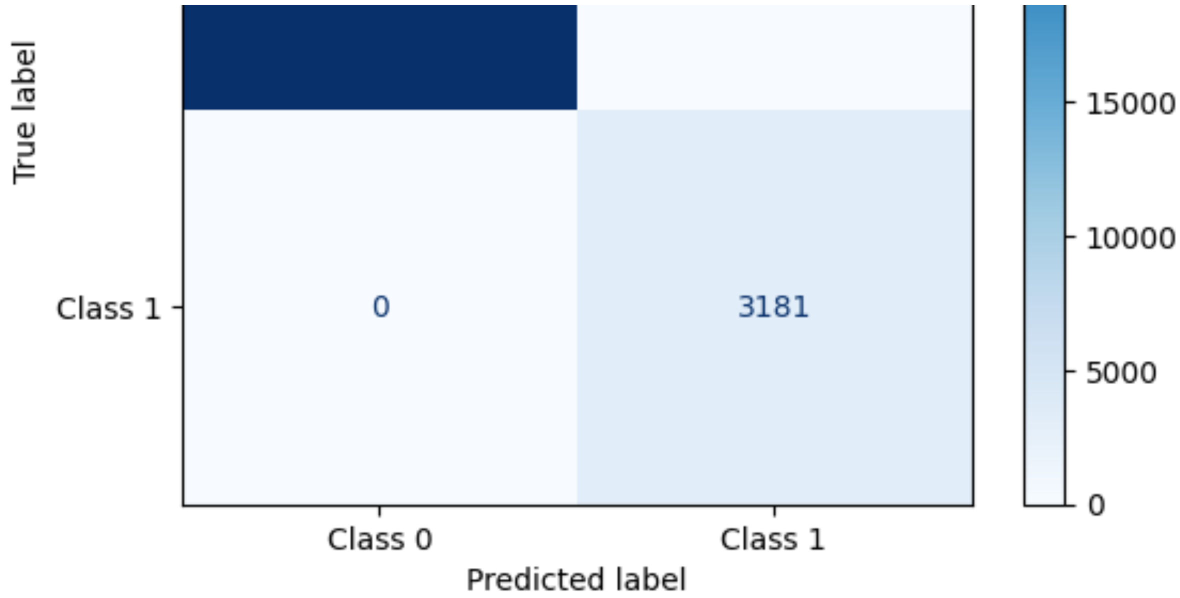
Random Forest (Train) - Confusion Matrix

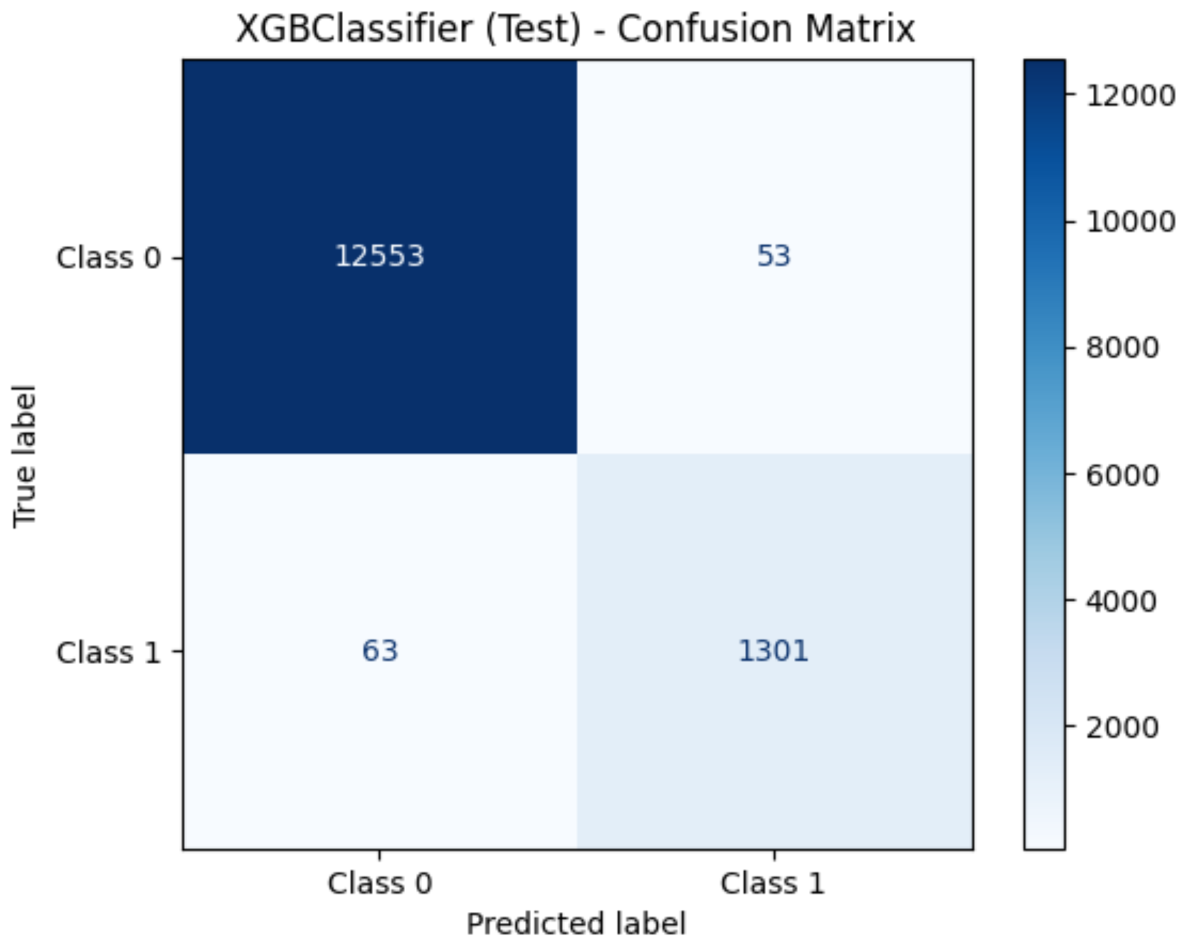


Random Forest (Test) - Confusion Matrix



XGBClassifier (Train) - Confusion Matrix





Export for Deployment

Model to be Deployed

```
# Save the best model
joblib.dump(xgb_best_model, 'model.pkl')

# Download/export the best model
files.download('model.pkl')
```

Downloading "model.pkl":

SHAP Explainer

```
# Create SHAP explainer for your XGBoost model
explainer = shap.TreeExplainer(xgb_model)

# Save explainer to file
with open('explainer.pkl', 'wb') as f:
    pickle.dump(explainer, f)

# Download/export the SHAP explainer
files.download('explainer.pkl')
```

Downloading "explainer.pkl":