Empowering Financial Insights: Predicting Customer Transactions with Advanced Machine Learning

In this notebook, we aim to predict whether customers will make a specific transaction in the future using machine learning techniques. Our approach involves various data preprocessing techniques and model building strategies to optimize performance. We will explore multiple model versions, each with different strategies for handling the data and feature engineering.

```
In [2]: import numpy as np
         import pandas as pd
         from xgboost import XGBClassifier
         from lightgbm import LGBMClassifier
         from sklearn.model_selection import StratifiedKFold, GridSearchCV
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import f1_score, roc_auc_score, roc_curve, accuracy_score, cla
         from sklearn.decomposition import PCA
         import matplotlib.pyplot as plt
         import seaborn as sns
         import joblib
In [3]: train = pd.read_csv(r"train.csv")
         test = pd.read csv(r"test.csv")
In [4]:
         train.sample(10)
Out[4]:
                      ID_code target
                                         var 0
                                                  var 1
                                                           var 2
                                                                  var 3
                                                                            var 4
                                                                                     var 5
                                                                                             var 6
         126291
                  train_126291
                                        7.1061
                                                 2.5162
                                                          9.7902
                                                                 9.1782
                                                                         10.1327
                                                                                    -2.1839
                                                                                            4.3226
                                    1
                                                         15.6593
          44068
                   train 44068
                                       14.6245
                                                 0.7622
                                                                  7.4749
                                                                          11.2130
                                                                                    -9.0417
                                                                                            4.8924
          65269
                   train_65269
                                       17.5887
                                                -4.2776
                                                         12.3604
                                                                  4.5615
                                                                          12.8307
                                                                                    -4.7195
                                                                                            5.4608
          94036
                   train 94036
                                        9.0451
                                               -5.3304
                                                         12.3644
                                                                  6.8955
                                                                          11.3978
                                                                                    -3.8517
                                                                                            5.4273
                                                                                    8.5718 5.9157
          62832
                                      14.0789
                                                -6.6696
                                                        12.0120
                                                                  6.4697
                                                                          10.8467
                   train 62832
          41362
                   train 41362
                                       10.3317
                                                -0.3173
                                                         15.2826
                                                                  8.4846
                                                                          13.4219
                                                                                   -16.5936
                                                                                            5.8558
          36245
                   train 36245
                                       11.1535
                                                 2.5683
                                                        14.3768
                                                                  3.5758
                                                                         10.8850
                                                                                    -2.2093
                                                                                           6.3655
         184062
                  train 184062
                                       15.5129
                                                -4.1668
                                                          9.6569
                                                                  5.8974
                                                                          11.0991
                                                                                   -12.0629
                                                                                            4.0331
            6260
                    train 6260
                                        9.8054
                                                -3.5607
                                                          9.0193
                                                                  7.8273
                                                                         11.7178
                                                                                           6.5975
                                                                                    0.8777
          70774
                   train 70774
                                      10.7270
                                                 1.2081
                                                          8.5852 7.7302
                                                                           9.3600
                                                                                    7.9731 4.0607
```

10 rows × 202 columns

```
In [5]: # Analysis
train.shape, test.shape
```

```
Out[5]: ((200000, 202), (200000, 201))
```

In [6]: train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Columns: 202 entries, ID_code to var_199
dtypes: float64(200), int64(1), object(1)

memory usage: 308.2+ MB

In [7]: train.describe()

() i i ± 1	7	
Out	/	

	target	var_0	var_1	var_2	var_3	
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.
mean	0.100490	10.679914	-1.627622	10.715192	6.796529	11.
std	0.300653	3.040051	4.050044	2.640894	2.043319	1.
min	0.000000	0.408400	-15.043400	2.117100	-0.040200	5.
25%	0.000000	8.453850	-4.740025	8.722475	5.254075	9.
50%	0.000000	10.524750	-1.608050	10.580000	6.825000	11.
75%	0.000000	12.758200	1.358625	12.516700	8.324100	12.
max	1.000000	20.315000	10.376800	19.353000	13.188300	16.

8 rows × 201 columns



Data Preprocessing: Optimizing Features for Better Predictions

In order to prepare the data for modeling, we must clean and optimize it. Our data preprocessing steps include:

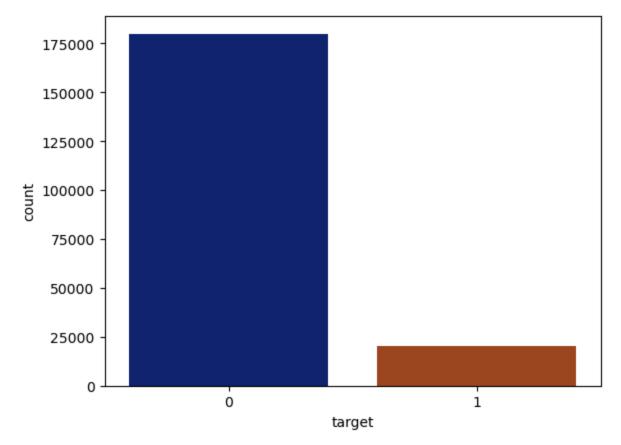
- 1. **Dropping the ID column:** The ID_code column is not useful for prediction.
- 2. **Handling missing values:** We fill any missing values with the mean of the respective feature to maintain data integrity.
- 3. **Removing highly correlated features:** To reduce multicollinearity, we eliminate features with a correlation higher than 0.9. This ensures that redundant features do not negatively affect model performance.

The clean_train() function is responsible for these steps.

```
In [9]: # check duplicates
train.duplicated().sum()
```

Out[9]: 0

Out[11]: <Axes: xlabel='target', ylabel='count'>



```
In [12]: # Clean and preprocess the train
def clean_train(df, corr_threshold=0.9):
    # Drop ID column (not useful for prediction)
    df = df.drop(columns=['ID_code'])

# Check for null values and fill if necessary
    df.fillna(df.mean(), inplace=True)

# Drop highly correlated features (correlation threshold > 0.9)
    corr_matrix = df.corr().abs()
```

```
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool)
    to_drop = [column for column in upper.columns if any(upper[column] > corr_thres

    df = df.drop(columns=to_drop)
        return df

In [13]: # Clean train
    df = clean_train(train)

In [14]: X = df.drop(columns=['target']).values
    y = df['target']
```

Version 1: Baseline Model Without Fake Rows

In this version, we build a baseline model using only the original training data without any artificial (fake) rows added. This serves as a control to understand the performance of a simple model before introducing more sophisticated techniques.

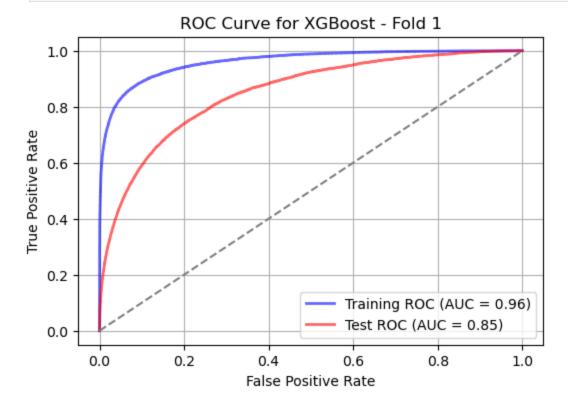
- We clean the training data using the clean train() function.
- The baseline model is built using XGBoost and LightGBM, two popular gradient boosting algorithms.
- Performance metrics such as AUC-ROC and F1 score are used to evaluate the model.

```
In [16]: def train_and_evaluate_models_v1(X, y, n_splits=2):
             skf = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=42)
             models = {
                 'XGBoost': XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=6,
                 'LightGBM': LGBMClassifier(learning_rate=0.04, num_leaves=31, max_bin=1023,
             }
             fold_metrics = {name: {'accuracy': [], 'f1_score': [], 'roc_auc': []} for name
             mean_fpr = np.linspace(0, 1, 100)
             tpr_list_train = {name: [] for name in models.keys()}
             tpr_list_test = {name: [] for name in models.keys()}
             fold_number = 1
             for train index, test index in skf.split(X, y):
                 X_train, X_test = X[train_index], X[test_index]
                 y_train, y_test = y.iloc[train_index], y.iloc[test_index]
                 scaler = StandardScaler()
                 X_train_scaled = scaler.fit_transform(X_train)
                 X_test_scaled = scaler.transform(X_test)
                 for name, model in models.items():
                     model.fit(X_train_scaled, y_train)
                     y_train_pred = model.predict( X_train_scaled)
                     y_train_pred_prob = model.predict_proba( X_train_scaled)[:, 1]
                     train_accuracy = accuracy_score(y_train, y_train_pred)
                     train_f1 = f1_score(y_train, y_train_pred)
                     train_auc = roc_auc_score(y_train, y_train_pred_prob)
```

```
y_test_pred = model.predict(X_test_scaled)
        y test pred prob = model.predict proba(X test scaled)[:, 1]
        test_accuracy = accuracy_score(y_test, y_test_pred)
        test_f1 = f1_score(y_test, y_test_pred)
        test_auc = roc_auc_score(y_test, y_test_pred_prob)
        fold_metrics[name]['accuracy'].append(test_accuracy)
        fold metrics[name]['f1 score'].append(test f1)
        fold_metrics[name]['roc_auc'].append(test_auc)
        fpr_train, tpr_train, _ = roc_curve(y_train, y_train_pred_prob)
        fpr_test, tpr_test, _ = roc_curve(y_test, y_test_pred_prob)
        tpr_list_train[name].append(np.interp(mean_fpr, fpr_train, tpr_train))
        tpr list train[name][-1][0] = 0.0
        tpr_list_test[name].append(np.interp(mean_fpr, fpr_test, tpr_test))
        tpr_list_test[name][-1][0] = 0.0
        plt.figure(figsize=(6, 4))
        plt.plot(fpr_train, tpr_train, color='blue', label=f'Training ROC (AUC
        plt.plot(fpr_test, tpr_test, color='red', label=f'Test ROC (AUC = {test
        plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title(f'ROC Curve for {name} - Fold {fold_number}')
        plt.legend(loc='lower right')
        plt.grid()
        plt.show()
        print(f"{name} Fold {fold_number} Metrics:")
        print(f"Training Accuracy: {train_accuracy:.2f}, Test Accuracy: {test_a
        print(f"Training F1 Score: {train_f1:.2f}, Test F1 Score: {test_f1:.2f}
        print(f"Training AUC: {train_auc:.2f}, Test AUC: {test_auc:.2f}")
        print(f"Classification Report for Test Set:\n{classification_report(y_t
        if abs(train_auc - test_auc) > 0.10:
            print("Warning: Possible Overfitting Detected")
    fold number += 1
plt.figure(figsize=(6, 4))
for name in models.keys():
    mean_tpr_train = np.mean(tpr_list_train[name], axis=0)
    mean_tpr_train[-1] = 1.0
   mean_auc_train = auc(mean_fpr, mean_tpr_train)
    plt.plot(mean_fpr, mean_tpr_train, lw=2, linestyle='-', label=f'{name} Mean
   mean_tpr_test = np.mean(tpr_list_test[name], axis=0)
   mean\_tpr\_test[-1] = 1.0
   mean_auc_test = auc(mean_fpr, mean_tpr_test)
    plt.plot(mean_fpr, mean_tpr_test, lw=2, linestyle='-', label=f'{name} Mean
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Final Mean ROC Curve for All Models')
plt.legend(loc='lower right')
plt.grid()
```

```
for name, metrics in fold_metrics.items():
    final_accuracy = np.mean(metrics['accuracy'])
    final_f1 = np.mean(metrics['f1_score'])
    final_roc_auc = np.mean(metrics['roc_auc'])
    print(f"\n{name} Final Cross-Validation Metrics:")
    print(f"Final Accuracy: {final_accuracy:.2f}")
    print(f"Final F1 Score: {final_f1:.2f}")
    print(f"Final ROC AUC: {final_roc_auc:.2f}")
```

In [17]: models, scaler = train_and_evaluate_models_v1(X, y)



XGBoost Fold 1 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.45, Test F1 Score: 0.17

Training AUC: 0.96, Test AUC: 0.85 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	89951
1	0.85	0.10	0.17	10049
accuracy			0.91	100000
macro avg	0.88	0.55	0.56	100000
weighted avg	0.90	0.91	0.87	100000

Warning: Possible Overfitting Detected

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 10049, number of negative: 89951

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.281139 seconds.

You can set `force col wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 203987

[LightGBM] [Info] Number of data points in the train set: 100000, number of used fea tures: 200

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.100490 -> initscore=-2.191792

[LightGBM] [Info] Start training from score -2.191792

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

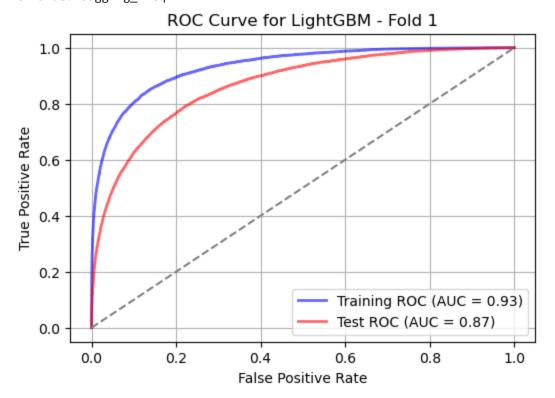
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

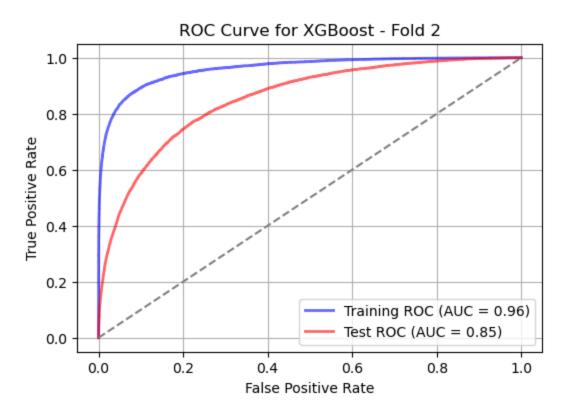
[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1



LightGBM Fold 1 Metrics:

Training Accuracy: 0.91, Test Accuracy: 0.90 Training F1 Score: 0.22, Test F1 Score: 0.11

support	f1-score	recall	precision	
89951	0.95	1.00	0.90	0
10049	0.11	0.06	0.92	1
100000	0.90			accuracy
100000	0.53	0.53	0.91	macro avg
100000	0.87	0.90	0.91	weighted avg



XGBoost Fold 2 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.44, Test F1 Score: 0.17

Training AUC: 0.96, Test AUC: 0.85 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.01	1 00	0.05	90051
0	0.91	1.00	0.95	89951
1	0.84	0.09	0.17	10049
accuracy			0.91	100000
macro avg	0.87	0.54	0.56	100000
weighted avg	0.90	0.91	0.87	100000

Warning: Possible Overfitting Detected

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 10049, number of negative: 89951

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.378510 seconds.

You can set `force col wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 203985

[LightGBM] [Info] Number of data points in the train set: 100000, number of used fea tures: 200

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.100490 -> initscore=-2.191792

[LightGBM] [Info] Start training from score -2.191792

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

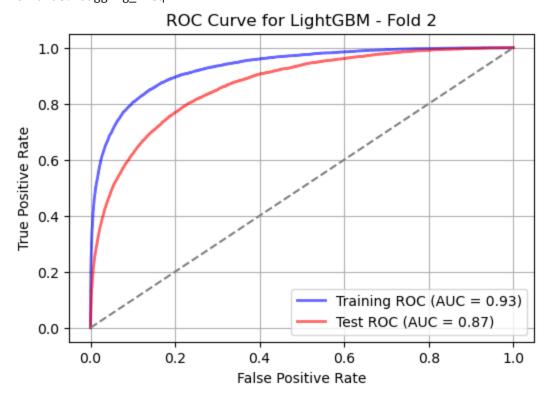
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

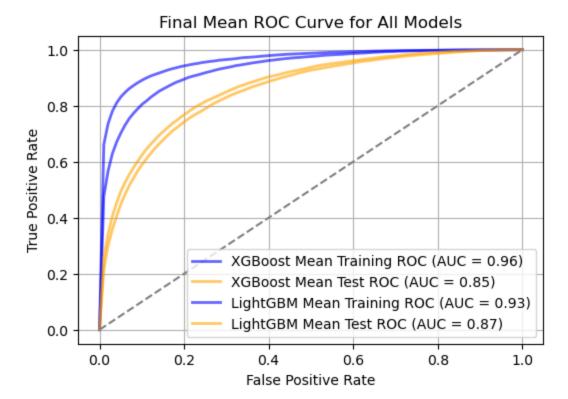
[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1



LightGBM Fold 2 Metrics:

Training Accuracy: 0.91, Test Accuracy: 0.90 Training F1 Score: 0.22, Test F1 Score: 0.11

	precision	recall	f1-score	support
0	0.90	1.00	0.95	89951
1	0.90	0.06	0.11	10049
accuracy			0.90	100000
macro avg	0.90	0.53	0.53	100000
weighted avg	0.90	0.90	0.86	100000



XGBoost Final Cross-Validation Metrics:

Final Accuracy: 0.91 Final F1 Score: 0.17 Final ROC AUC: 0.85

LightGBM Final Cross-Validation Metrics:

Final Accuracy: 0.90 Final F1 Score: 0.11 Final ROC AUC: 0.87

In []:

Version 2: Model with Cleaned Dataset (Without PCA)

In this version, we focus on cleaning the dataset by removing duplicate rows and outliers before training the model. We do **not** apply Principal Component Analysis (PCA) in this version, opting to retain the full feature set.

- **Data Cleaning:** We ensure the integrity of the dataset by checking for and removing duplicate rows and outliers (using z-scores). This helps improve the model's performance by eliminating noisy or abnormal data points that could negatively affect learning.
- **Model Training:** We use the same gradient boosting algorithms as before, but now train the models on this cleaned dataset. The goal is to assess how the model performs without dimensionality reduction through PCA and with a more refined dataset.

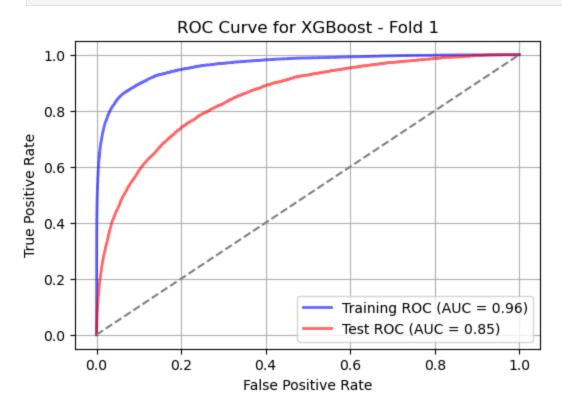
```
In [19]: # Check for fake rows based on duplicated rows or abnormal values
    def check_fake_rows(df):
        # Check for duplicate rows
```

```
duplicate_rows = df[df.duplicated()]
             print(f"Number of duplicate rows: {len(duplicate_rows)}")
             if len(duplicate rows) > 0:
                 print("Duplicate rows found:\n", duplicate_rows)
                 df = df.drop_duplicates()
             # Check for outliers in the train using z-score
             from scipy.stats import zscore
             z scores = np.abs(df.apply(zscore))
             df = df[(z_scores < 3).all(axis=1)]</pre>
             outliers = (z_scores > 3).sum().sum()
             print(f"Number of potential outliers (removed) (z-score > 3): {outliers}")
             return df
In [20]: # Check for fake rows
         df1 = check_fake_rows(df)
        Number of duplicate rows: 0
        Number of potential outliers (removed) (z-score > 3): 11299
In [21]: # Prepare features and target
         X_1 = df1.drop(columns=['target']).values
         y_1 = df1['target']
In [22]: def train_and_evaluate_models_v2(X, y, n_splits=2):
             skf = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=42)
             models = {
                  'XGBoost': XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=6,
                  'LightGBM': LGBMClassifier(learning_rate=0.04, num_leaves=31, max_bin=1023,
             fold_metrics = {name: {'accuracy': [], 'f1_score': [], 'roc_auc': []} for name
             mean_fpr = np.linspace(0, 1, 100)
             tpr_list_train = {name: [] for name in models.keys()}
             tpr_list_test = {name: [] for name in models.keys()}
             fold_number = 1
             for train_index, test_index in skf.split(X, y):
                 X_train, X_test = X[train_index], X[test_index]
                 y_train, y_test = y.iloc[train_index], y.iloc[test_index]
                 scaler = StandardScaler()
                 X_train_scaled = scaler.fit_transform(X_train)
                 X_test_scaled = scaler.transform(X_test)
                 for name, model in models.items():
                     model.fit(X_train_scaled, y_train)
                     y_train_pred = model.predict( X_train_scaled)
                     y_train_pred_prob = model.predict_proba( X_train_scaled)[:, 1]
                     train_accuracy = accuracy_score(y_train, y_train_pred)
                     train_f1 = f1_score(y_train, y_train_pred)
                     train_auc = roc_auc_score(y_train, y_train_pred_prob)
                     y test pred = model.predict(X test scaled)
                     y_test_pred_prob = model.predict_proba(X_test_scaled)[:, 1]
```

```
test_accuracy = accuracy_score(y_test, y_test_pred)
        test_f1 = f1_score(y_test, y_test_pred)
        test auc = roc auc score(y test, y test pred prob)
        fold_metrics[name]['accuracy'].append(test_accuracy)
        fold_metrics[name]['f1_score'].append(test_f1)
        fold_metrics[name]['roc_auc'].append(test_auc)
        fpr_train, tpr_train, _ = roc_curve(y_train, y_train_pred_prob)
        fpr_test, tpr_test, _ = roc_curve(y_test, y_test_pred_prob)
        tpr_list_train[name].append(np.interp(mean_fpr, fpr_train, tpr_train))
        tpr_list_train[name][-1][0] = 0.0
        tpr_list_test[name].append(np.interp(mean_fpr, fpr_test, tpr_test))
        tpr_list_test[name][-1][0] = 0.0
        plt.figure(figsize=(6, 4))
        plt.plot(fpr_train, tpr_train, color='blue', label=f'Training ROC (AUC
        plt.plot(fpr_test, tpr_test, color='red', label=f'Test ROC (AUC = {test
        plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title(f'ROC Curve for {name} - Fold {fold_number}')
        plt.legend(loc='lower right')
        plt.grid()
        plt.show()
        print(f"{name} Fold {fold_number} Metrics:")
        print(f"Training Accuracy: {train_accuracy:.2f}, Test Accuracy: {test_a
        print(f"Training F1 Score: {train_f1:.2f}, Test F1 Score: {test_f1:.2f}
        print(f"Training AUC: {train_auc:.2f}, Test AUC: {test_auc:.2f}")
        print(f"Classification Report for Test Set:\n{classification_report(y_t
        if abs(train_auc - test_auc) > 0.10:
            print("Warning: Possible Overfitting Detected")
    fold number += 1
plt.figure(figsize=(6, 4))
for name in models.keys():
    mean_tpr_train = np.mean(tpr_list_train[name], axis=0)
    mean_tpr_train[-1] = 1.0
   mean_auc_train = auc(mean_fpr, mean_tpr_train)
    plt.plot(mean_fpr, mean_tpr_train, lw=2, linestyle='-', label=f'{name} Mean
   mean_tpr_test = np.mean(tpr_list_test[name], axis=0)
   mean tpr test[-1] = 1.0
    mean_auc_test = auc(mean_fpr, mean_tpr_test)
    plt.plot(mean_fpr, mean_tpr_test, lw=2, linestyle='-', label=f'{name} Mean
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Final Mean ROC Curve for All Models')
plt.legend(loc='lower right')
plt.grid()
plt.show()
for name, metrics in fold metrics.items():
```

```
final_accuracy = np.mean(metrics['accuracy'])
  final_f1 = np.mean(metrics['f1_score'])
  final_roc_auc = np.mean(metrics['roc_auc'])
  print(f"\n{name} Final Cross-Validation Metrics:")
  print(f"Final Accuracy: {final_accuracy:.2f}")
  print(f"Final F1 Score: {final_f1:.2f}")
  print(f"Final ROC AUC: {final_roc_auc:.2f}")
```

In [23]: train_and_evaluate_models_v2(X_1, y_1)



XGBoost Fold 1 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.45, Test F1 Score: 0.16

Training AUC: 0.96, Test AUC: 0.85 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	85072
1	0.84	0.09	0.16	9413
accuracy			0.91	94485
macro avg weighted avg	0.88 0.90	0.54 0.91	0.56 0.87	94485 94485

Warning: Possible Overfitting Detected

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 9413, number of negative: 85071

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.280382 seconds.

You can set `force col wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 203980

[LightGBM] [Info] Number of data points in the train set: 94484, number of used feat ures: 200

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.099625 -> initscore=-2.201394

[LightGBM] [Info] Start training from score -2.201394

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

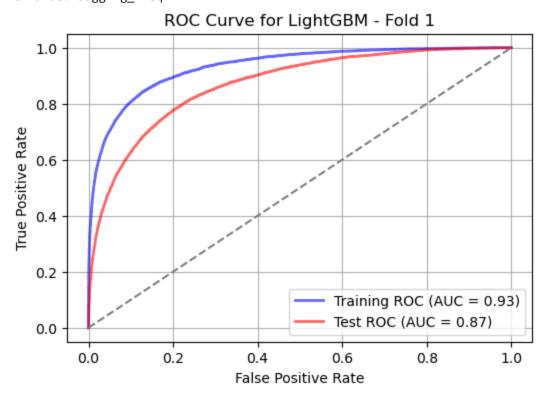
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

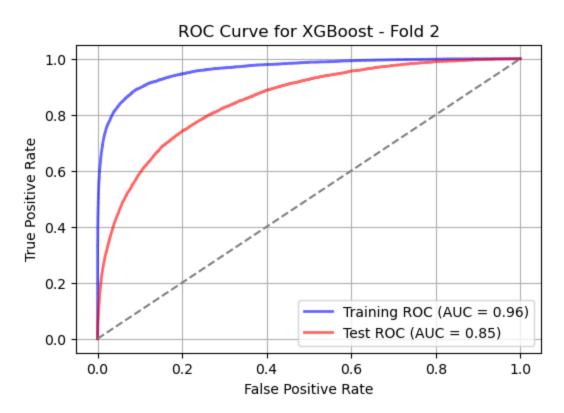
[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1



LightGBM Fold 1 Metrics:

Training Accuracy: 0.91, Test Accuracy: 0.91 Training F1 Score: 0.23, Test F1 Score: 0.10

support	f1-score	recall	precision	
85072	0.95	1.00	0.91	0
9413	0.10	0.05	0.90	1
94485	0.91			accuracy
94485	0.53	0.53	0.90	macro avg
94485	0.87	0.91	0.90	weighted avg



XGBoost Fold 2 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.46, Test F1 Score: 0.16

Training AUC: 0.96, Test AUC: 0.85 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	85071
1	0.83	0.09	0.16	9413
accuracy			0.91	94484
macro avg	0.87	0.54	0.55	94484
weighted avg	0.90	0.91	0.87	94484

Warning: Possible Overfitting Detected

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 9413, number of negative: 85072

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.280734 seconds.

You can set `force col wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 203979

[LightGBM] [Info] Number of data points in the train set: 94485, number of used feat ures: 200

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.099624 -> initscore=-2.201406

[LightGBM] [Info] Start training from score -2.201406

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

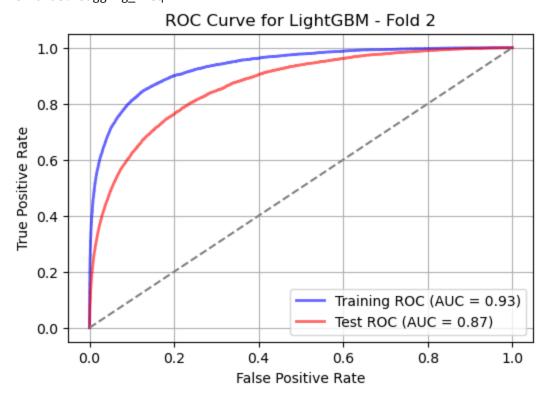
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

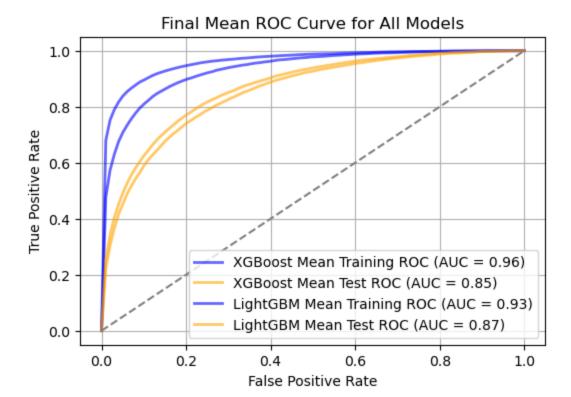
[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1



LightGBM Fold 2 Metrics:

Training Accuracy: 0.91, Test Accuracy: 0.91 Training F1 Score: 0.22, Test F1 Score: 0.11

support	f1-score	recall	precision	
85071	0.95	1.00	0.91	0
9413	0.11	0.06	0.90	1
94484	0.91			accuracy
94484	0.53	0.53	0.90	macro avg
94484	0.87	0.91	0.91	weighted avg



XGBoost Final Cross-Validation Metrics:

Final Accuracy: 0.91 Final F1 Score: 0.16 Final ROC AUC: 0.85

LightGBM Final Cross-Validation Metrics:

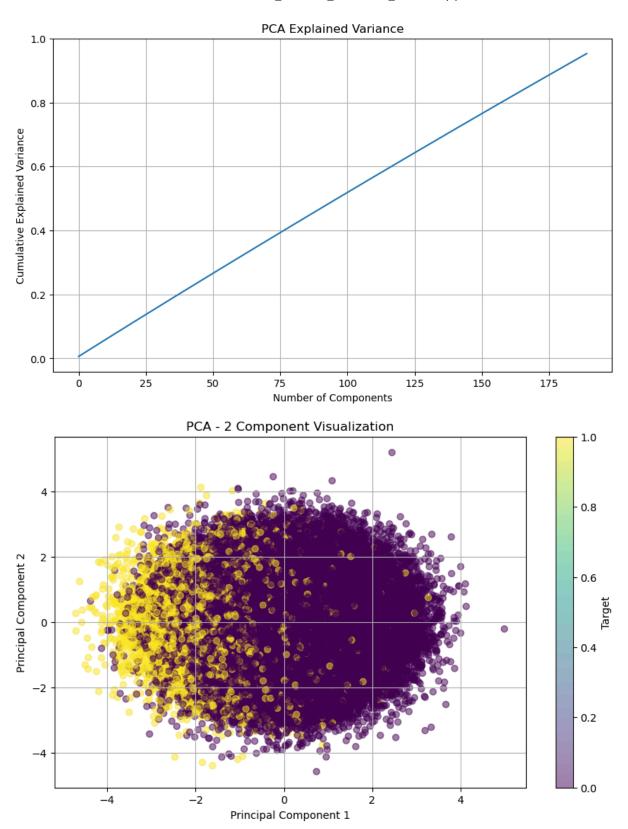
Final Accuracy: 0.91 Final F1 Score: 0.10 Final ROC AUC: 0.87

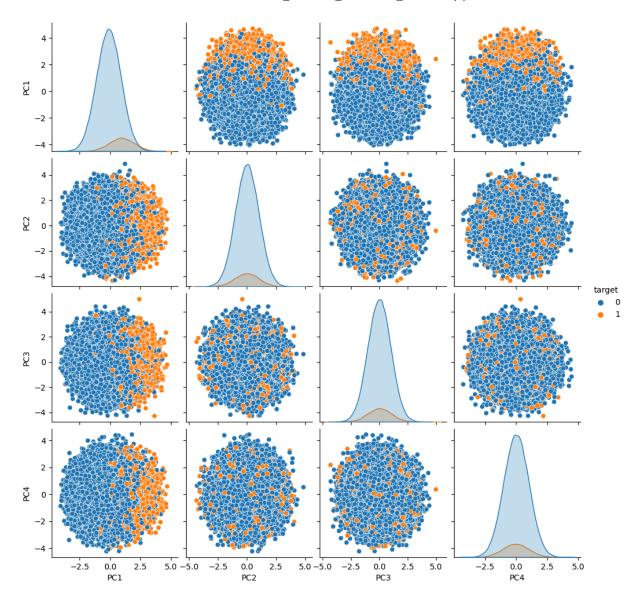
```
Out[23]: {'XGBoost': XGBClassifier(base score=None, booster=None, callbacks=None,
                         colsample_bylevel=None, colsample_bynode=None,
                         colsample_bytree=0.8, device=None, early_stopping_rounds=None,
                         enable categorical=False, eval metric='logloss',
                         feature types=None, gamma=None, grow policy=None,
                         importance_type=None, interaction_constraints=None,
                         learning rate=0.1, max bin=None, max cat threshold=None,
                         max_cat_to_onehot=None, max_delta_step=None, max_depth=6,
                         max_leaves=None, min_child_weight=None, missing=nan,
                         monotone_constraints=None, multi_strategy=None, n_estimators=100,
                         n jobs=None, num parallel tree=None, random state=42, ...),
           'LightGBM': LGBMClassifier(bagging_fraction=0.85, bagging_freq=1, feature_fractio
         n=1.0,
                          learning_rate=0.04, max_bin=1023, min_child_samples=1000,
                          n_estimators=200, n_jobs=-1, objective='binary', reg_alpha=0.1,
                          reg_lambda=0.2)}
```

PCA Visualization

This section presents the PCA (Principal Component Analysis) visualization to better understand the data.

```
In [26]: # Apply PCA for dimensionality reduction
         def apply_pca(X_train, X_test, n_components=0.90):
             pca = PCA(n_components=n_components)
             X_train_pca = pca.fit_transform(X_train)
             X test pca = pca.transform(X test)
             return X_train_pca, X_test_pca, pca
In [27]: def visualize_pca_results(X, y):
             scaler = StandardScaler()
             X_scaled = scaler.fit_transform(X)
             # Fit PCA to explain 95% of the variance
             pca = PCA(n components=0.95)
             X_pca = pca.fit_transform(X_scaled)
             # Explained variance plot
             plt.figure(figsize=(10, 6))
             plt.plot(np.cumsum(pca.explained_variance_ratio_))
             plt.xlabel('Number of Components')
             plt.ylabel('Cumulative Explained Variance')
             plt.title('PCA Explained Variance')
             plt.grid()
             plt.show()
             # 2D visualization of the first two principal components
             pca_2d = PCA(n_components=2)
             X_pca_2d = pca_2d.fit_transform(X_scaled)
             pca_df = pd.DataFrame(X_pca_2d, columns=['PC1', 'PC2'])
             pca_df['target'] = y.values
             plt.figure(figsize=(10, 6))
             plt.scatter(pca_df['PC1'], pca_df['PC2'], c=pca_df['target'], cmap='viridis', a
             plt.xlabel('Principal Component 1')
             plt.ylabel('Principal Component 2')
             plt.title('PCA - 2 Component Visualization')
             plt.colorbar(label='Target')
             plt.grid()
             plt.show()
             # Pairplot for the first four components
             pca_4d = PCA(n_components=4)
             X_pca_4d = pca_4d.fit_transform(X_scaled)
             pca_df_4d = pd.DataFrame(X_pca_4d, columns=['PC1', 'PC2', 'PC3', 'PC4'])
             pca df 4d['target'] = y.values
             sns.pairplot(pca_df_4d, hue='target', diag_kind='kde')
             plt.show()
In [28]:
          visualize_pca_results(X, y)
```





Version 3: Model with PCA

This version builds upon the previous one by applying **Principal Component Analysis** (**PCA**) to the dataset. PCA is used to reduce the dimensionality of the data while retaining most of the variance, which can improve both the model's training time and its performance by focusing on the most important features.

- **PCA Application:** we apply PCA to reduce the feature space while preserving the key variance in the dataset.
- **Model building:** The model is then trained using the transformed dataset (with reduced dimensions) to further improve performance.

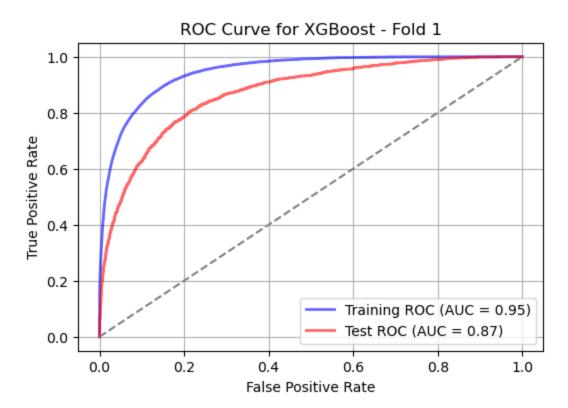
```
In [30]: # Model training function using StratifiedKFold

def train_and_evaluate_models_with_pca(X, y, n_splits=10):
    skf = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=43)
    models = {
        'XGBoost': XGBClassifier(n_estimators=300, learning_rate=0.06, max_depth=6,
```

```
'LightGBM': LGBMClassifier(learning_rate=0.06, num_leaves=31, max_bin=1023,
}
fold_metrics = {name: {'accuracy': [], 'f1_score': [], 'roc_auc': []} for name
mean_fpr = np.linspace(0, 1, 100)
tpr_list_train = {name: [] for name in models.keys()}
tpr_list_test = {name: [] for name in models.keys()}
fold number = 1
for train_index, test_index in skf.split(X, y):
   X_train, X_test = X[train_index], X[test_index]
   y_train, y_test = y.iloc[train_index], y.iloc[test_index]
    # Standardize the data
    scaler = StandardScaler()
   X_train_scaled = scaler.fit_transform(X_train)
   X_test_scaled = scaler.transform(X_test)
    # Apply PCA for dimensionality reduction.
   X_train_pca, X_test_pca, pca = apply_pca(X_train_scaled, X_test_scaled)
    for name, model in models.items():
        model.fit(X_train_pca, y_train)
        y_train_pred = model.predict(X_train_pca)
        y_train_pred_prob = model.predict_proba(X_train_pca)[:, 1]
        train_accuracy = accuracy_score(y_train, y_train_pred)
        train_f1 = f1_score(y_train, y_train_pred)
        train_auc = roc_auc_score(y_train, y_train_pred_prob)
        y_test_pred = model.predict(X_test_pca)
        y_test_pred_prob = model.predict_proba(X_test_pca)[:, 1]
        test_accuracy = accuracy_score(y_test, y_test_pred)
        test_f1 = f1_score(y_test, y_test_pred)
        test_auc = roc_auc_score(y_test, y_test_pred_prob)
        fold_metrics[name]['accuracy'].append(test_accuracy)
        fold_metrics[name]['f1_score'].append(test_f1)
        fold_metrics[name]['roc_auc'].append(test_auc)
        fpr_train, tpr_train, _ = roc_curve(y_train, y_train_pred_prob)
        fpr_test, tpr_test, _ = roc_curve(y_test, y_test_pred_prob)
        tpr_list_train[name].append(np.interp(mean_fpr, fpr_train, tpr_train))
        tpr list_train[name][-1][0] = 0.0
        tpr_list_test[name].append(np.interp(mean_fpr, fpr_test, tpr_test))
        tpr_list_test[name][-1][0] = 0.0
        plt.figure(figsize=(6, 4))
        plt.plot(fpr_train, tpr_train, color='blue', label=f'Training ROC (AUC
        plt.plot(fpr_test, tpr_test, color='red', label=f'Test ROC (AUC = {test
        plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title(f'ROC Curve for {name} - Fold {fold_number}')
        plt.legend(loc='lower right')
        plt.grid()
        plt.show()
```

```
print(f"{name} Fold {fold_number} Metrics:")
        print(f"Training Accuracy: {train accuracy:.2f}, Test Accuracy: {test a
        print(f"Training F1 Score: {train_f1:.2f}, Test F1 Score: {test_f1:.2f}
        print(f"Training AUC: {train_auc:.2f}, Test AUC: {test_auc:.2f}")
        print(f"Classification Report for Test Set:\n{classification_report(y_t
        if abs(train_auc - test_auc) > 0.10:
            print("Warning: Possible Overfitting Detected")
    fold number += 1
plt.figure(figsize=(6, 4))
for name in models.keys():
    mean_tpr_train = np.mean(tpr_list_train[name], axis=0)
    mean_tpr_train[-1] = 1.0
    mean auc train = auc(mean fpr, mean tpr train)
    plt.plot(mean_fpr, mean_tpr_train, lw=2, linestyle='-', label=f'{name} Mean
   mean_tpr_test = np.mean(tpr_list_test[name], axis=0)
   mean\_tpr\_test[-1] = 1.0
    mean_auc_test = auc(mean_fpr, mean_tpr_test)
    plt.plot(mean_fpr, mean_tpr_test, lw=2, linestyle='-', label=f'{name} Mean
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Final Mean ROC Curve for All Models')
plt.legend(loc='lower right')
plt.grid()
plt.show()
for name, metrics in fold metrics.items():
    final_accuracy = np.mean(metrics['accuracy'])
    final_f1 = np.mean(metrics['f1_score'])
    final roc auc = np.mean(metrics['roc auc'])
    print(f"\n{name} Final Cross-Validation Metrics:")
    print(f"Final Accuracy: {final_accuracy:.2f}")
    print(f"Final F1 Score: {final f1:.2f}")
    print(f"Final ROC AUC: {final_roc_auc:.2f}")
return models, pca, scaler
```

```
In [31]: # Train and evaluate models using StratifiedKFold
models, pca, scaler = train_and_evaluate_models_with_pca(X, y)
```



XGBoost Fold 1 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.92 Training F1 Score: 0.54, Test F1 Score: 0.40

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.95	17991
1	0.69	0.28	0.40	2009
accuracy			0.92	20000
macro avg	0.81	0.63	0.68	20000
weighted avg	0.90	0.92	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18089, number of negative: 161911

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.492916 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

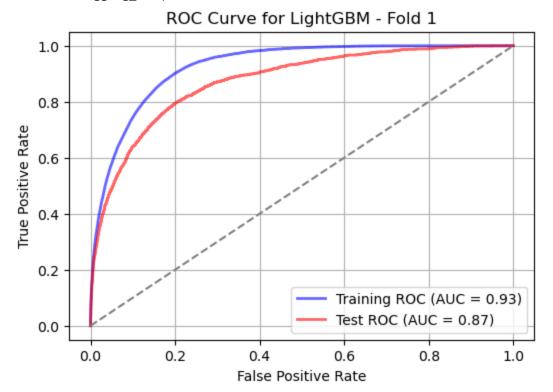
[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu

rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

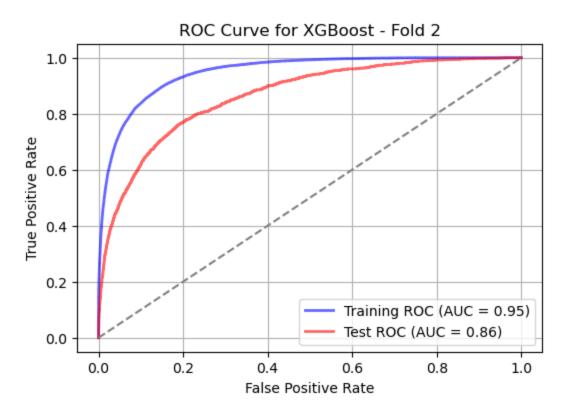
t value: bagging_freq=1



LightGBM Fold 1 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.46

	precision	recall	f1-score	support
0	0.97	0.83	0.89	17991
1	0.33	0.76	0.46	2009
			0.00	20000
accuracy			0.82	20000
macro avg	0.65	0.79	0.68	20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Fold 2 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.54, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.86 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.95	17991
1	0.70	0.27	0.39	2009
accuracy			0.91	20000
macro avg weighted avg	0.81 0.90	0.63 0.91	0.67 0.90	20000 20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18089, number of negative: 161911

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.429686 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

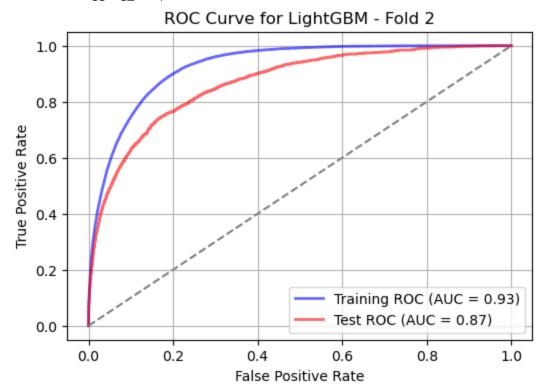
[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu

rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

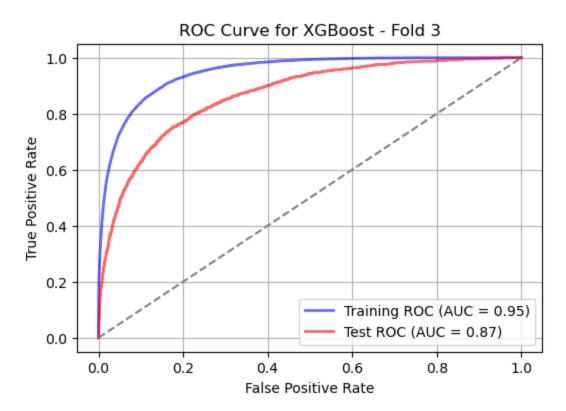
t value: bagging_freq=1



LightGBM Fold 2 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.45

	precision	recall	f1-score	support
0	0.97	0.83	0.89	17991
1	0.32	0.75	0.45	2009
2661112614			0.82	20000
accuracy macro avg	0.65	0.79	0.67	20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Fold 3 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.54, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.98	0.95	17990
1	0.66	0.28	0.39	2010
accuracy			0.91	20000
macro avg	0.79	0.63	0.67	20000
weighted avg	0.90	0.91	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.428401 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

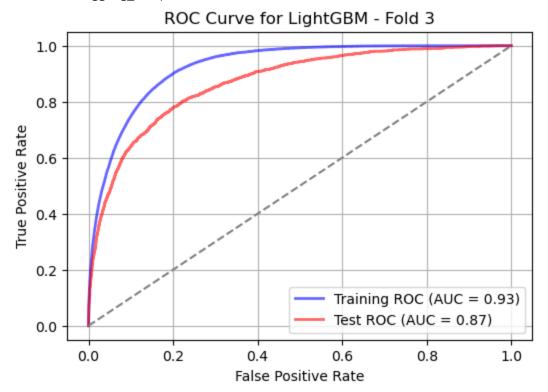
[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu

rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

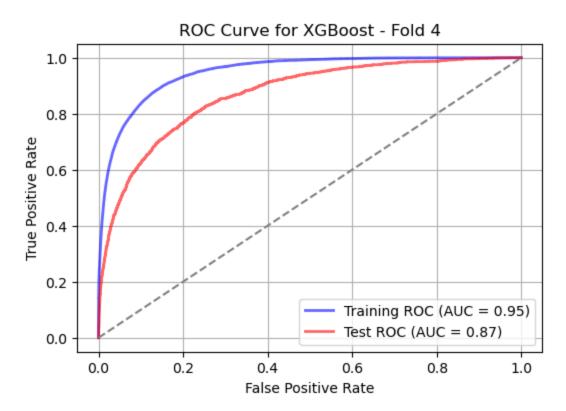
t value: bagging_freq=1



LightGBM Fold 3 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.45

	precision	recall	f1-score	support
0	0.97	0.82	0.89	17990
1	0.32	0.75	0.45	2010
266412264			0.00	20000
accuracy macro avg	0.65	0.79	0.82 0.67	20000 20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Fold 4 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.54, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.95	17990
1	0.69	0.27	0.39	2010
accuracy			0.91	20000
macro avg	0.81	0.63	0.67	20000
weighted avg	0.90	0.91	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.461017 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

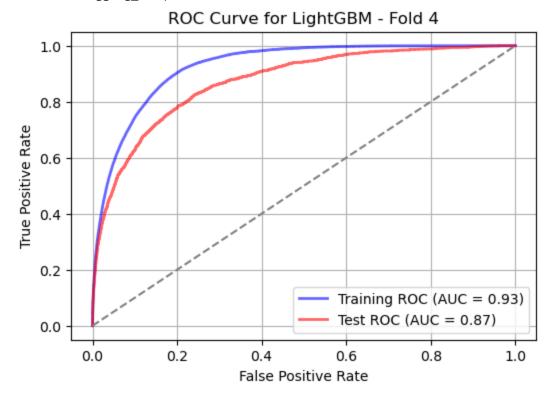
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

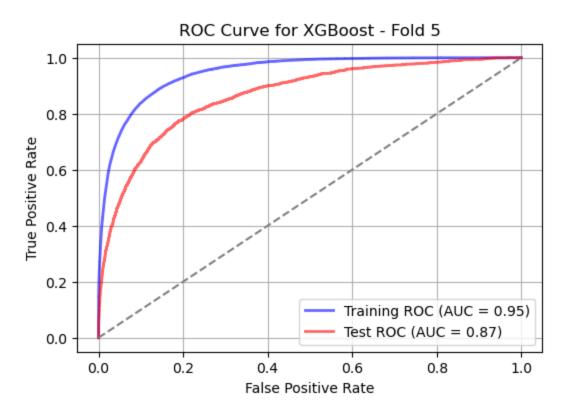
t value: bagging_freq=1



LightGBM Fold 4 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.83 Training F1 Score: 0.52, Test F1 Score: 0.46

	precision	recall	f1-score	support
0	0.97	0.84	0.90	17990
1	0.34	0.73	0.46	2010
266110261			0.83	20000
accuracy macro avg	0.65	0.79	0.68	20000
weighted avg	0.90	0.83	0.85	20000



XGBoost Fold 5 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.92 Training F1 Score: 0.54, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.95	17990
1	0.70	0.27	0.39	2010
accuracy			0.92	20000
macro avg	0.81	0.63	0.67	20000
weighted avg	0.90	0.92	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.436246 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

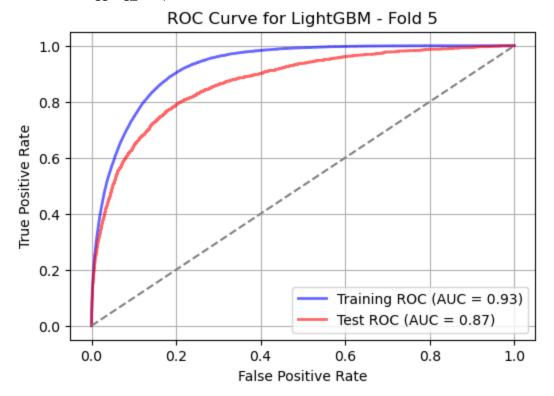
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

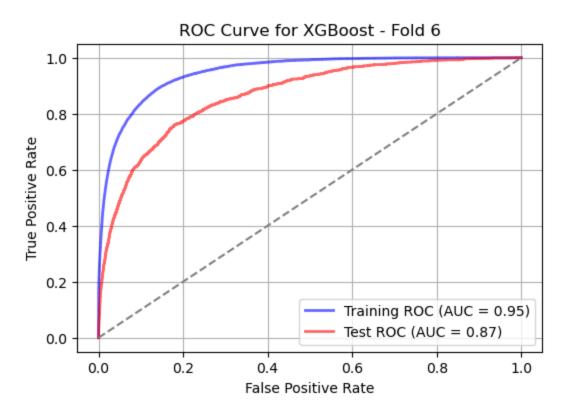
t value: bagging_freq=1



LightGBM Fold 5 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.83 Training F1 Score: 0.52, Test F1 Score: 0.46

	precision	recall	f1-score	support
0	0.97	0.84	0.90	17990
1	0.34	0.75	0.46	2010
accuracy			0.83	20000
macro avg	0.65	0.79	0.68	20000
weighted avg	0.90	0.83	0.85	20000



XGBoost Fold 6 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.53, Test F1 Score: 0.40

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

		precision	recall	f1-score	support
	0	0.92	0.98	0.95	17990
	1	0.67	0.28	0.40	2010
accurac	V			0.91	20000
macro av	-	0.80	0.63	0.67	20000
weighted av	g	0.90	0.91	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.438750 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used fea tures: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

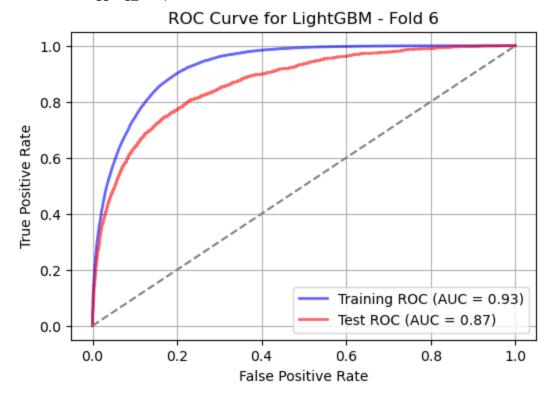
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

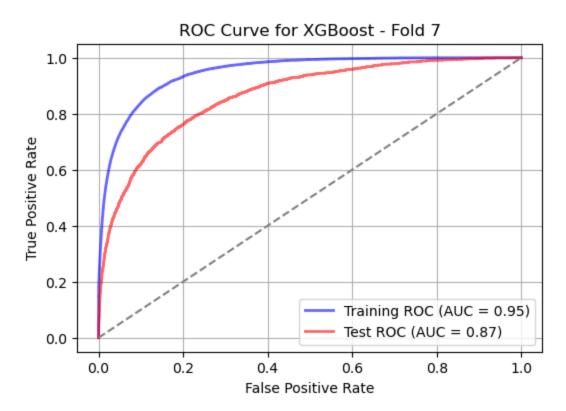
t value: bagging_freq=1



LightGBM Fold 6 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.46

support	f1-score	recall	precision	
17990	0.89	0.83	0.97	0
2010	0.46	0.74	0.33	1
20000	0.82			accuracy
20000	0.68	0.79	0.65	macro avg
20000	0.85	0.82	0.90	weighted avg



XGBoost Fold 7 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.92 Training F1 Score: 0.53, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.87 Classification Report for Test Set:

	precision	recall	f1-score	support
0 1	0.92 0.71	0.99 0.27	0.95 0.39	17990 2010
accuracy macro avg weighted avg	0.82 0.90	0.63 0.92	0.92 0.67 0.90	20000 20000 20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.448420 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used fea tures: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

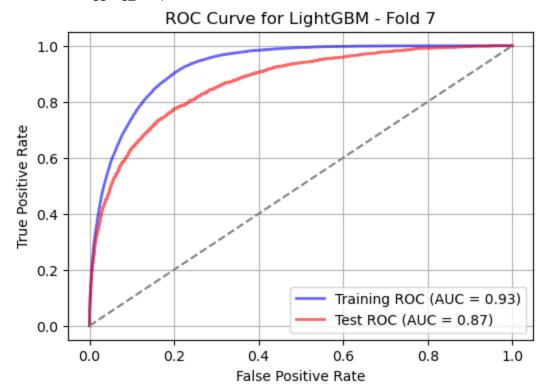
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

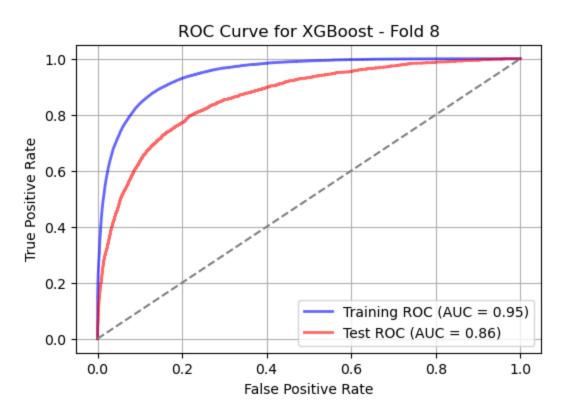
t value: bagging_freq=1



LightGBM Fold 7 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.45

	precision	recall	f1-score	support
0	0.97	0.83	0.89	17990
_				
1	0.33	0.74	0.45	2010
accuracy			0.82	20000
macro avg	0.65	0.78	0.67	20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Fold 8 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.91 Training F1 Score: 0.53, Test F1 Score: 0.38

Training AUC: 0.95, Test AUC: 0.86 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.95	17990
1	0.69	0.27	0.38	2010
accuracy			0.91	20000
macro avg	0.80	0.63	0.67	20000
weighted avg	0.90	0.91	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.479569 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used fea tures: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

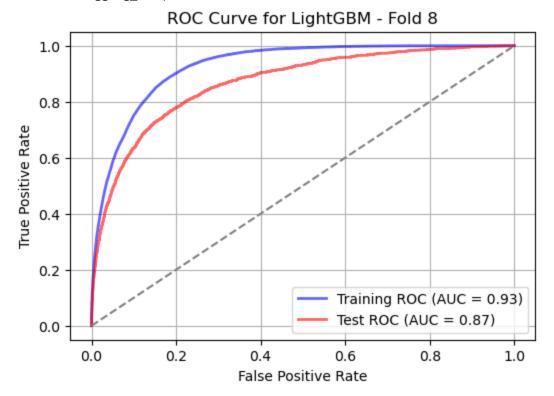
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

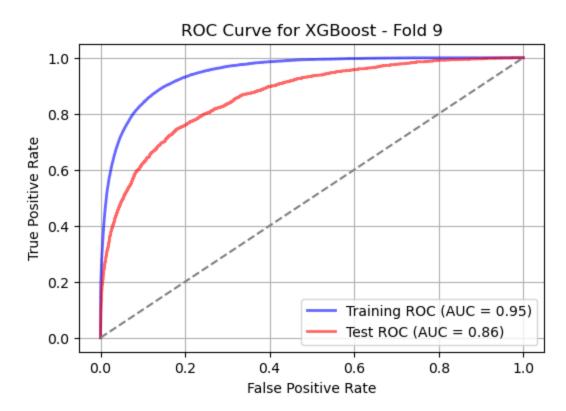
t value: bagging_freq=1



LightGBM Fold 8 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.83 Training F1 Score: 0.52, Test F1 Score: 0.46

	precision	recall	f1-score	support
0	0.97	0.84	0.90	17990
1	0.33	0.74	0.46	2010
			0.02	20000
accuracy	0.65	0.79	0.83	20000 20000
macro avg	0.65 0.90	0.79	0.68	20000
weighted avg	0.90	0.83	0.85	20000



XGBoost Fold 9 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.92 Training F1 Score: 0.53, Test F1 Score: 0.41

Training AUC: 0.95, Test AUC: 0.86 Classification Report for Test Set:

	precision	recall	f1-score	support
0	0.92	0.99	0.96	17990
1	0.72	0.28	0.41	2010
accuracy			0.92	20000
macro avg	0.82	0.64	0.68	20000
weighted avg	0.90	0.92	0.90	20000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.502708 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used fea tures: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Current value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

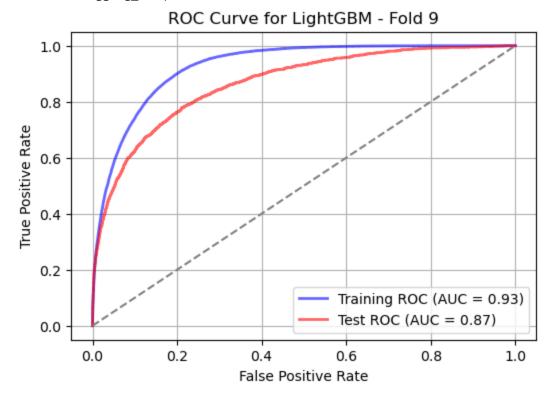
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

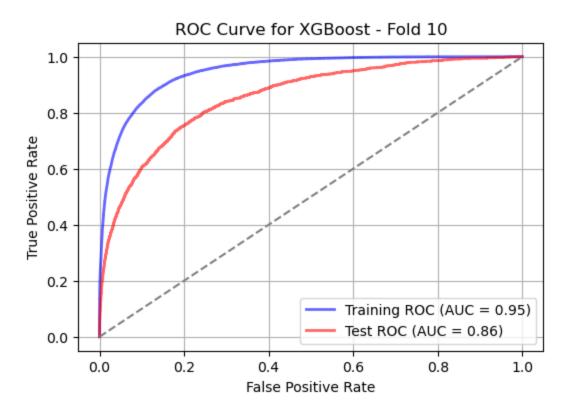
t value: bagging_freq=1



LightGBM Fold 9 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.45

	precision	recall	f1-score	support
0	0.96	0.84	0.90	17990
1	0.33	0.72	0.45	2010
accuracy			0.82	20000
macro avg	0.65	0.78	0.67	20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Fold 10 Metrics:

Training Accuracy: 0.93, Test Accuracy: 0.92 Training F1 Score: 0.54, Test F1 Score: 0.39

Training AUC: 0.95, Test AUC: 0.86 Classification Report for Test Set:

precision	recall	f1-score	support
0.92	0.99	0.95	17990
0.71	0.27	0.39	2010
		0.92	20000
0.82	0.63	0.67	20000
0.90	0.92	0.90	20000
	0.92 0.71 0.82	0.92 0.99 0.71 0.27 0.82 0.63	0.92 0.99 0.95 0.71 0.27 0.39 0.92 0.82 0.63 0.67

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Info] Number of positive: 18088, number of negative: 161912

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.401765 seconds.

You can set `force_col_wise=true` to remove the overhead.

[LightGBM] [Info] Total Bins 183117

[LightGBM] [Info] Number of data points in the train set: 180000, number of used features: 179

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

[LightGBM] [Info] Start training from score 0.000000

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

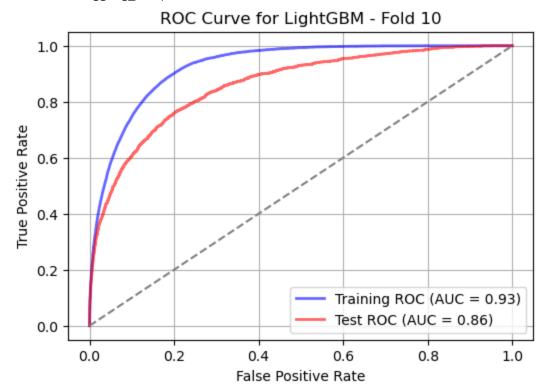
[LightGBM] [Warning] bagging_fraction is set=0.85, subsample=1.0 will be ignored. Cu rrent value: bagging_fraction=0.85

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren t value: bagging_freq=1

[LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ignor ed. Current value: feature_fraction=1.0

[LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curren

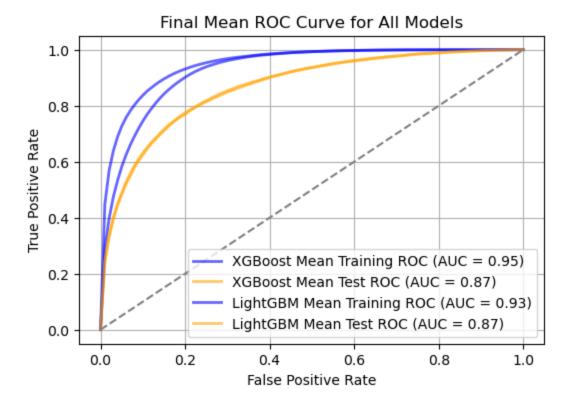
t value: bagging_freq=1



LightGBM Fold 10 Metrics:

Training Accuracy: 0.84, Test Accuracy: 0.82 Training F1 Score: 0.52, Test F1 Score: 0.44

	precision	recall	f1-score	support
0	0.96	0.83	0.89	17990
1	0.32	0.72	0.44	2010
accuracy			0.82	20000
macro avg	0.64	0.77	0.67	20000
weighted avg	0.90	0.82	0.85	20000



XGBoost Final Cross-Validation Metrics:

Final Accuracy: 0.91 Final F1 Score: 0.39 Final ROC AUC: 0.87

LightGBM Final Cross-Validation Metrics:

Final Accuracy: 0.82 Final F1 Score: 0.46 Final ROC AUC: 0.87

Saving Models and Preprocessing Objects

To use the trained models and preprocessing components later, we save them to disk:

```
In [33]: # Save the models, PCA, and scaler to disk
    joblib.dump(models['XGBoost'], r'E:\my_work\dpi\New folder (2)\xgboost_model.pkl')
    joblib.dump(models['LightGBM'], r'E:\my_work\dpi\New folder (2)\lightgbm_model.pkl'
    joblib.dump(pca, r'E:\my_work\dpi\New folder (2)\pca.pkl')
    joblib.dump(scaler, r'E:\my_work\dpi\New folder (2)\scaler.pkl')
```

Out[33]: ['E:\\my_work\\dpi\\New folder (2)\\scaler.pkl']

Making Test Predictions and Saving Results

The following code cleans the test data, applies scaling and PCA, makes predictions using the trained models, and saves the results:

In [35]: # Function to make predictions on the test set and save the output

```
def make test predictions(models, scaler, pca):
              # Clean the test data (note that test data doesn't have 'target' column)
              test_cleaned = test.drop(columns=['ID_code']).copy()
              # Handle any missing values in test data similarly to training data
              test_cleaned.fillna(test_cleaned.mean(), inplace=True)
              # Apply scaling to the test data
              test_scaled = scaler.transform(test_cleaned)
              # Apply PCA to the scaled test data
              test_pca = pca.transform(test_scaled)
              # Predict probabilities using trained models and save results
              id_codes = test['ID_code']
              results_df = pd.DataFrame({'ID_code': id_codes})
              # Assuming you want to make predictions using all models
              for name, model in models.items():
                  predictions = model.predict proba(test pca)[:, 1]
                  results_df[f'{name}_predicted_probabilities'] = predictions
              # Save the results to a CSV file
              results_df.to_csv(r'E:\my_work\dpi\predictions_with_id.csv', index=False)
              # Display the first few rows of the results for verification
              print(results_df.head())
In [36]: make_test_predictions(models, scaler, pca)
        C:\Users\Ahmed\anaconda3\Lib\site-packages\sklearn\base.py:457: UserWarning: X has
        feature names, but StandardScaler was fitted without feature names
          warnings.warn(
        [LightGBM] [Warning] feature_fraction is set=1.0, colsample_bytree=1.0 will be ign
        ored. Current value: feature_fraction=1.0
        [LightGBM] [Warning] bagging fraction is set=0.85, subsample=1.0 will be ignored.
        Current value: bagging_fraction=0.85
        [LightGBM] [Warning] bagging_freq is set=1, subsample_freq=0 will be ignored. Curr
        ent value: bagging_freq=1
          ID_code XGBoost_predicted_probabilities LightGBM_predicted_probabilities
        0 test 0
                                           0.178332
                                                                             0.655680
        1 test_1
                                           0.213811
                                                                             0.700468
        2 test 2
                                          0.052674
                                                                             0.361664
        3 test 3
                                          0.156415
                                                                             0.676556
        4 test_4
                                          0.053082
                                                                             0.250669
```