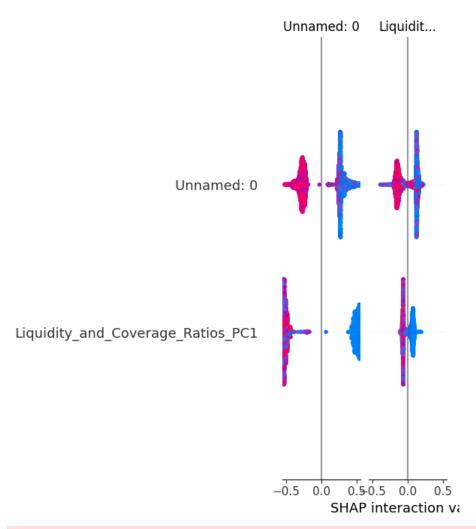
```
In [ ]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
         import datetime as dt
         import time
        import os
        import shap
        import lime
        from lime import lime_tabular
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearchCV
        from sklearn.preprocessing import MinMaxScaler
        import statsmodels.api as sm
        from sklearn.linear_model import LogisticRegression
        from sklearn.feature_selection import RFE
        from statsmodels.stats.outliers_influence import variance_inflation_factor
        from sklearn import metrics
        from sklearn.metrics import confusion_matrix
        from sklearn.metrics import precision score, recall score
        from sklearn.metrics import precision_recall_curve
        from sklearn.cluster import KMeans
        import missingno as msno
        from fancyimpute import IterativeImputer as MICE
        from sklearn.impute import IterativeImputer
        \textbf{from} \  \, \textbf{sklearn.ensemble} \  \, \textbf{import} \  \, \textbf{RandomForestClassifier}, \  \, \textbf{GradientBoostingClassifier}
        from sklearn.linear_model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.naive_bayes import GaussianNB
        from sklearn.svm import SVC
        import tensorflow as tf
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Input, Dense
        from tensorflow.keras.optimizers import Adam
        from sklearn.cluster import DBSCAN
        from imblearn.over_sampling import SMOTE
        from sklearn.neighbors import NearestNeighbors
        from collections import Counter
        from sklearn.decomposition import PCA
        import matplotlib.pyplot as plt
        import numpy as np
        from imblearn.over_sampling import KMeansSMOTE
        from sklearn.mixture import GaussianMixture
        from xgboost import XGBClassifier
        from rgf.sklearn import RGFClassifier # Regularized Greedy Forest
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense
        from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, roc_auc_score, roc_curve
        from sklearn.preprocessing import StandardScaler
        from sklearn.pipeline import Pipeline
        from joblib import dump, load
        import logging
In [ ]: logging.basicConfig(level=logging.INFO, format='%(asctime)s - %(levelname)s - %(message)s')
```

```
def split_dataset(dataset, target_column, test_size=0.2):
    Split dataset into training and testing sets.
   X = dataset.drop(columns=[target column])
   y = dataset[target_column]
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=42, stratify=y)
   logging.info("Dataset has been split and returned")
    return X_train, X_test, y_train, y_test
def train_ann(X_train, y_train):
   Train an Artificial Neural Network (ANN) on the training data.
    start_time = time.time()
   model = Sequential([
       Input(shape=(X_train.shape[1],)),
        Dense(12, activation='relu'),
        Dense(8, activation='relu'),
        Dense(1, activation='sigmoid')
   ])
   model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    model.fit(X_train, y_train, epochs=150, batch_size=10, verbose=0)
    end_time = time.time()
    logging.info(f"ANN has been trained in {end_time - start_time:.2f} seconds")
    return model
def train_models(X_train, y_train):
   Train multiple models on the training data.
    models = {}
    param_grids = {
        'RandomForest': {
            'n_estimators': [100, 200, 300],
            'max_depth': [None, 10, 20],
            'min_samples_split': [2, 5]
        'XGBoost': {
            'n_estimators': [100, 200, 300],
            'max_depth': [3, 6],
            'learning_rate': [0.01, 0.1]
        },
        'SVM': {
            'C': [0.1, 1, 10],
            'kernel': ['linear', 'rbf']
        'LogisticRegression': {
            'C': [0.1, 1, 10],
            'penalty': ['12']
        'GradientBoosting': {
            'n estimators': [100, 200, 300],
            'learning_rate': [0.01, 0.1],
            'max_depth': [3, 5, 7]
        }.
        'KNN': {
            'n_neighbors': [3, 5, 7],
            'weights': ['uniform', 'distance']
   }
   models['ANN'] = train_ann(X_train, y_train)
    for model_name, param_grid in param_grids.items():
        start_time = time.time()
        try:
            if model_name == 'RandomForest':
                model = GridSearchCV(RandomForestClassifier(), param_grid, cv=5)
            elif model_name == 'XGBoost':
               model = GridSearchCV(XGBClassifier(), param_grid, cv=5)
            elif model_name == 'SVM':
                model = GridSearchCV(SVC(probability=True), param_grid, cv=5)
```

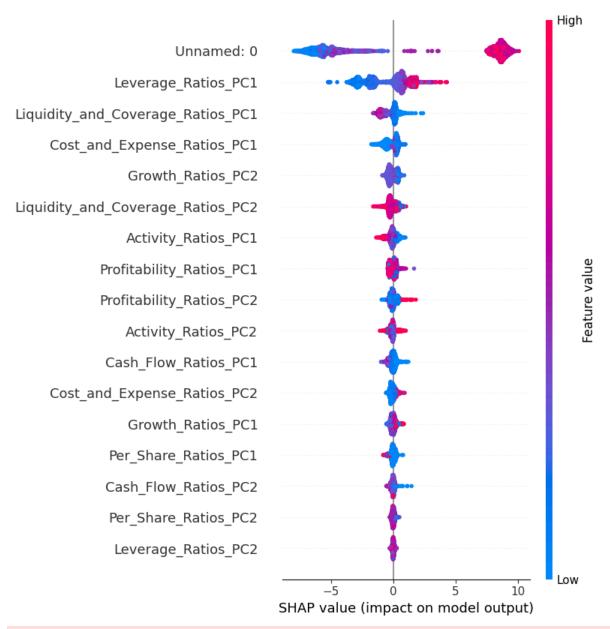
```
elif model_name == 'LogisticRegression':
               model = GridSearchCV(LogisticRegression(), param_grid, cv=5)
            elif model_name == 'GradientBoosting':
                model = GridSearchCV(GradientBoostingClassifier(), param_grid, cv=5)
            elif model name == 'KNN':
                model = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5)
            model.fit(X_train, y_train)
            models[model_name] = model.best_estimator_
            end_time = time.time()
            logging.info(f"{model_name} has been trained in {end_time - start_time:.2f} seconds")
        except Exception as e:
            logging.error(f"Error training {model name}: {e}")
   try:
        start_time = time.time()
        nb = GaussianNB()
        nb.fit(X_train, y_train)
        models['NaiveBayes'] = nb
        end time = time.time()
       logging.info(f"Naive Bayes has been trained in {end_time - start_time:.2f} seconds")
    except Exception as e:
       logging.error(f"Error training Naive Bayes: {e}")
    return models
def test_models(models, X_test):
    Test trained models on the test data.
   start_time = time.time()
    predictions = {}
   for name, model in models.items():
        try:
            if name == 'ANN':
                predictions[name] = (model.predict(X_test) > 0.5).astype("int32")
                predictions[name] = model.predict(X_test)
        except Exception as e:
            logging.error(f"Error testing {name}: {e}")
    end_time = time.time()
    logging.info(f"Models have been tested in {end_time - start_time:.2f} seconds")
    return predictions
def evaluate_models(models, predictions, y_test, X_test):
    Evaluate the performance of models.
   start_time = time.time()
    metrics = {}
    for name, y_pred in predictions.items():
        try:
            accuracy = accuracy_score(y_test, y_pred)
            cm = confusion_matrix(y_test, y_pred)
            f1 = f1_score(y_test, y_pred)
            auc = roc_auc_score(y_test, models[name].predict_proba(X_test)[:, 1]) if name != 'ANN' else roc_auc_score
            metrics[name] = {
                'accuracy': accuracy,
                'confusion matrix': cm,
                'f1_score': f1,
                'auc_roc': auc
        except Exception as e:
           logging.error(f"Error evaluating {name}: {e}")
    end_time = time.time()
    logging.info(f"Models have been evaluated in {end time - start time:.2f} seconds")
    return metrics
def explainability_shap(models, X_test, feature_names):
    Generate SHAP explanations for models.
    shap.initjs()
```

```
for name, model in models.items():
        if name == 'ANN':
            continue
        trv:
            explainer = shap.TreeExplainer(model)
            shap_values = explainer.shap_values(X_test)
            shap.summary_plot(shap_values, X_test, feature_names=feature_names)
            logging.info(f"SHAP summary plot for {name} created")
        except Exception as e:
            logging.error(f"Error generating SHAP explanations for {name}: {e}")
def explainability_lime(models, X_train, X_test, feature_names):
    Generate LIME explanations for models.
    explainer = lime.lime_tabular.LimeTabularExplainer(X_train, feature_names=feature_names, class_names=['class1',
    for name, model in models.items():
        if name == 'ANN':
            continue
        try:
            i = np.random.randint(0, X_test.shape[0])
            exp = explainer.explain_instance(X_test[i], model.predict_proba)
            exp.show_in_notebook(show_table=True)
            logging.info(f"LIME explanation for a sample of {name} created")
        except Exception as e:
            logging.error(f"Error generating LIME explanations for {name}: {e}")
def save_models(models, directory='models'):
    Save trained models to disk.
    if not os.path.exists(directory):
       os.makedirs(directory)
    for name, model in models.items():
       try:
            if name == 'ANN':
                model.save(os.path.join(directory, f'{name}_model.h5'))
            else:
                dump(model, os.path.join(directory, f'{name}_model.joblib'))
            logging.info(f"{name} model saved")
        except Exception as e:
            logging.error(f"Error saving {name} model: {e}")
def load_models(directory='models'):
    Load trained models from disk.
    models = \{\}
    for filename in os.listdir(directory):
        model_name, ext = os.path.splitext(filename)
           if ext == '.h5':
                models[model_name] = load_model(os.path.join(directory, filename))
            elif ext == '.joblib':
                models[model_name] = load(os.path.join(directory, filename))
            logging.info(f"{model_name} model loaded")
        except Exception as e:
            logging.error(f"Error loading {model_name} model: {e}")
    return models
def main(dataset, target_column):
   Main function to train, test, evaluate, and explain models.
   X_train, X_test, y_train, y_test = split_dataset(dataset, target_column)
   # Standardization
   scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
   X_test = scaler.transform(X_test)
   logging.info("Data has been standardized")
    models = train_models(X_train, y_train)
    predictions = test_models(models, X_test)
```

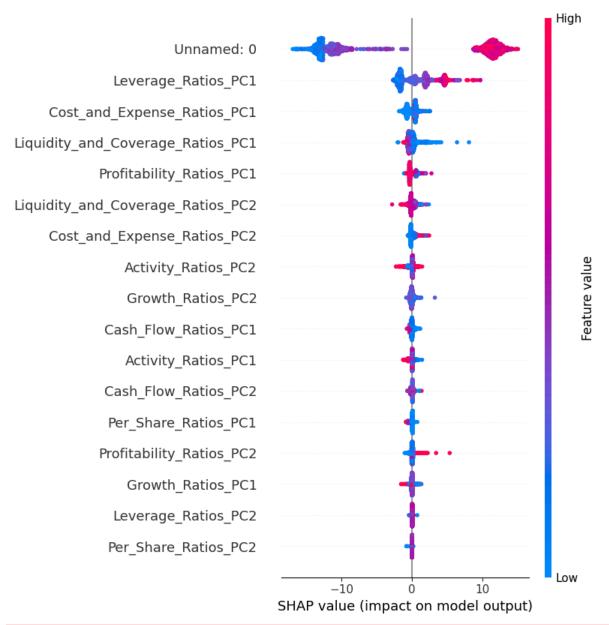
```
metrics = evaluate_models(models, predictions, y_test, X_test)
            explainability_shap(models, X_test, feature_names=dataset.drop(columns=[target_column]).columns)
            explainability_lime(models, X_train, X_test, feature_names=dataset.drop(columns=[target_column]).columns)
            save_models(models)
            logging.info("Models have been saved")
            return metrics
        def modelling_gs(df):
            Function to run the main pipeline with the given dataset.
            target_column = 'LABEL' # Replace with your target column
            results = main(df, target_column)
            logging.info(results)
            return results
        # To run the modelling function with a dataset 'df':
        # results = modelling_gs(df)
In [ ]: df_mice = pd.read_excel("C:\\Users\\dev\\Desktop\\Msc thesis Prior RS\\ML training\\df_mice_labeled_after_PCA.xlsx")
        df_AE = pd.read_excel("C:\\Users\\dev\\Desktop\\Msc thesis Prior RS\\ML training\\df_autoencoder_labeled_after_PCA.xi
In [ ]: results_mice = modelling_gs(df_mice)
        results_ae = modelling_gs(df_AE)
        print("Results for df_mice")
        print(f"{results_mice}")
        print(" ")
        print("_____
print(" ")
        print("Results for df AE")
        print(f"{results_ae}")
       2024-06-28 17:33:48,449 - INFO - Dataset has been split and returned
       2024-06-28 17:33:48,457 - INFO - Data has been standardized
       2024-06-28 17:35:47,950 - INFO - ANN has been trained in 119.49 seconds
       2024-06-28 17:43:06,218 - INFO - RandomForest has been trained in 438.27 seconds
       2024-06-28 17:43:16,772 - INFO - XGBoost has been trained in 10.55 seconds
       2024-06-28 17:45:22,266 - INFO - SVM has been trained in 125.49 seconds
       2024-06-28 17:45:22,611 - INFO - LogisticRegression has been trained in 0.35 seconds
       2024-06-28 18:17:28,288 - INFO - GradientBoosting has been trained in 1925.68 seconds
       2024-06-28 18:17:30,087 - INFO - KNN has been trained in 1.80 seconds
       2024-06-28 18:17:30,093 - INFO - Naive Bayes has been trained in 0.00 seconds
       126/126
                                   - 0s 685us/step
       2024-06-28 18:17:30,770 - INFO - Models have been tested in 0.68 seconds
       126/126 -
                                   0s 527us/step
       2024-06-28 18:17:31,453 - INFO - Models have been evaluated in 0.68 seconds
```



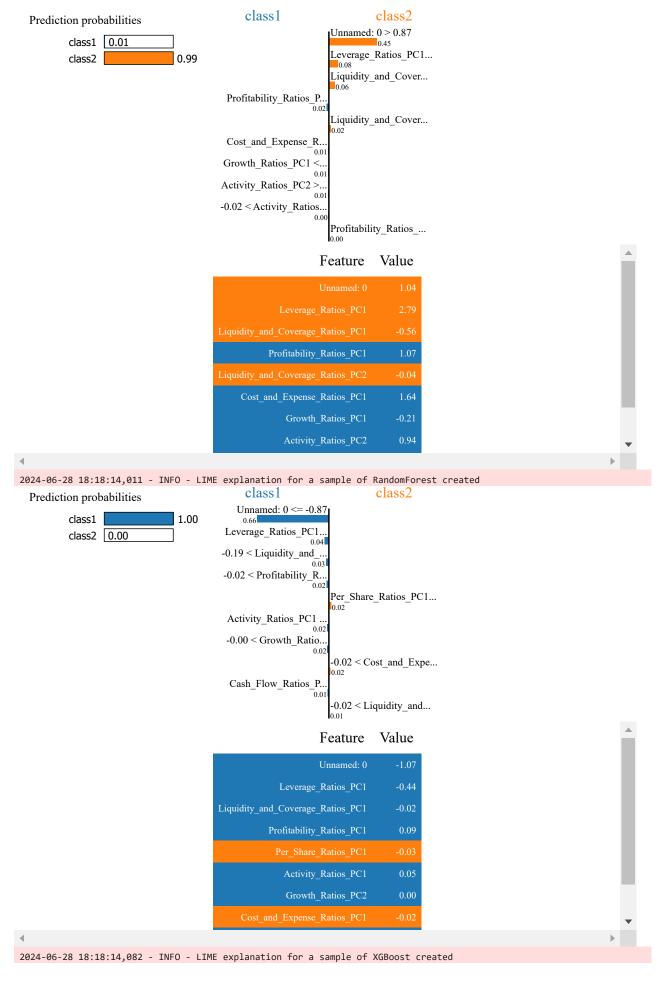
2024-06-28 18:18:02,647 - INFO - SHAP summary plot for RandomForest created

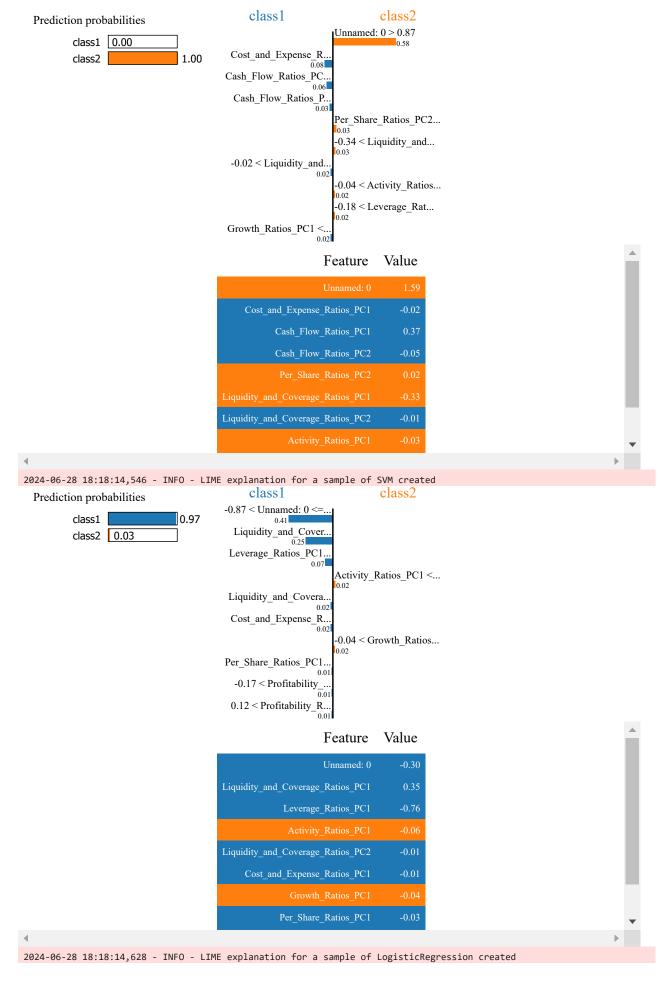


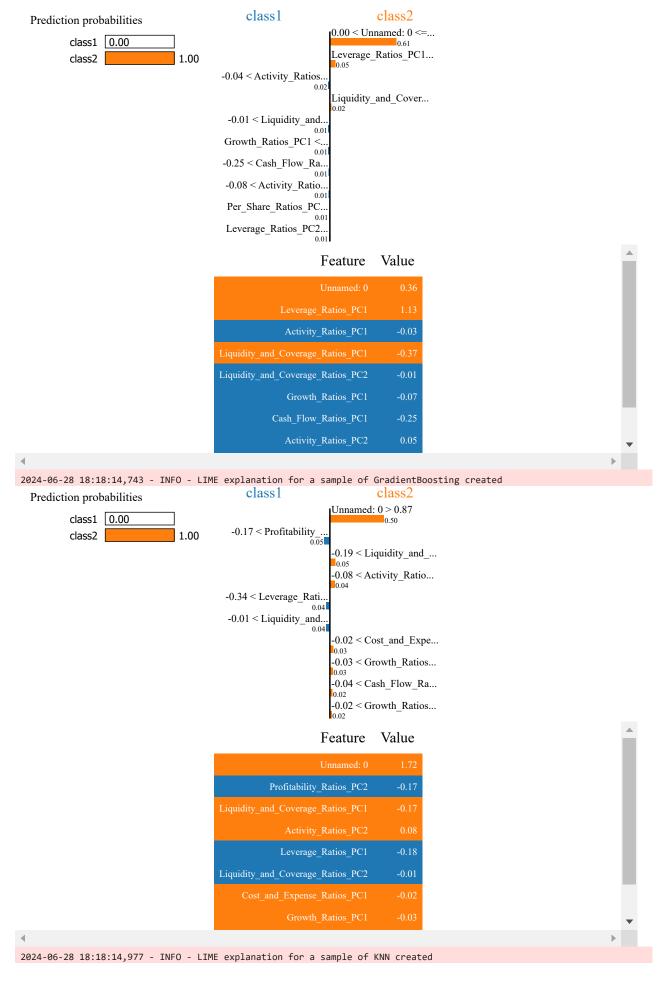
2024-06-28 18:18:03,822 - INFO - SHAP summary plot for XGBoost created
2024-06-28 18:18:03,822 - ERROR - Error generating SHAP explanations for SVM: Model type not yet supported by TreeExp lainer: <class 'sklearn.svm._classes.SVC'>
2024-06-28 18:18:03,823 - ERROR - Error generating SHAP explanations for LogisticRegression: Model type not yet supported by TreeExplainer: <class 'sklearn.linear_model._logistic.LogisticRegression'>

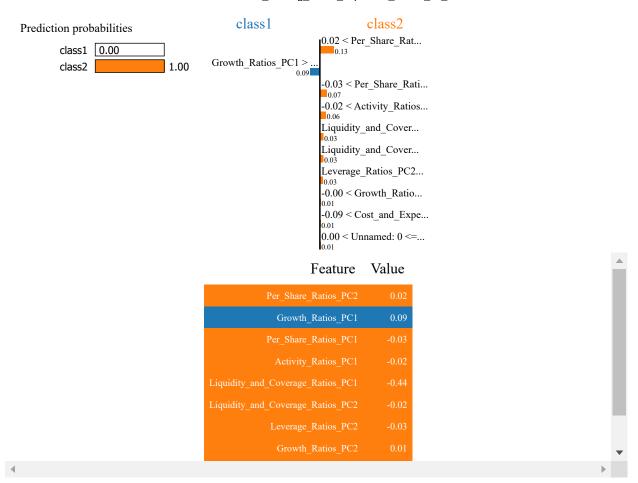


2024-06-28 18:18:13,847 - INFO - SHAP summary plot for GradientBoosting created
2024-06-28 18:18:13,847 - ERROR - Error generating SHAP explanations for KNN: Model type not yet supported by TreeExp
lainer: <class 'sklearn.neighbors._classification.KNeighborsClassifier'>
2024-06-28 18:18:13,848 - ERROR - Error generating SHAP explanations for NaiveBayes: Model type not yet supported by
TreeExplainer: <class 'sklearn.naive_bayes.GaussianNB'>

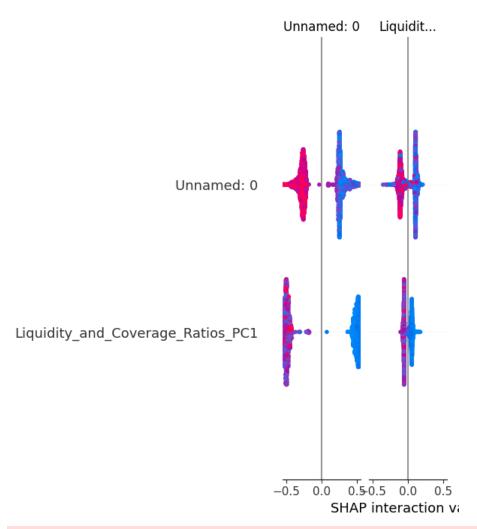




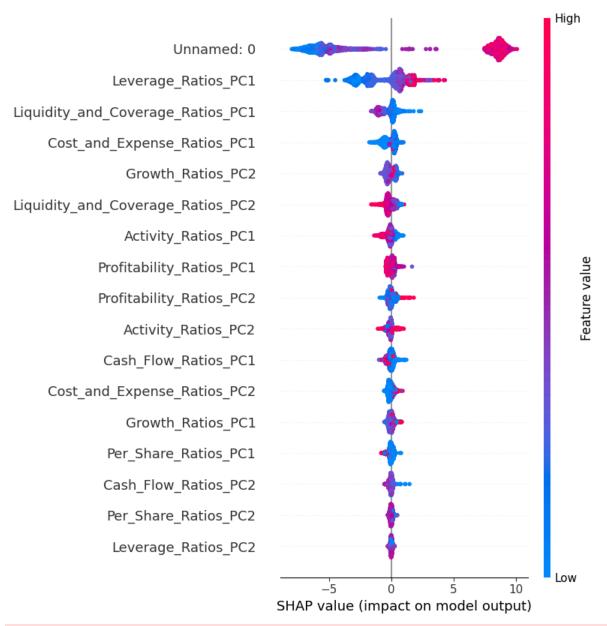




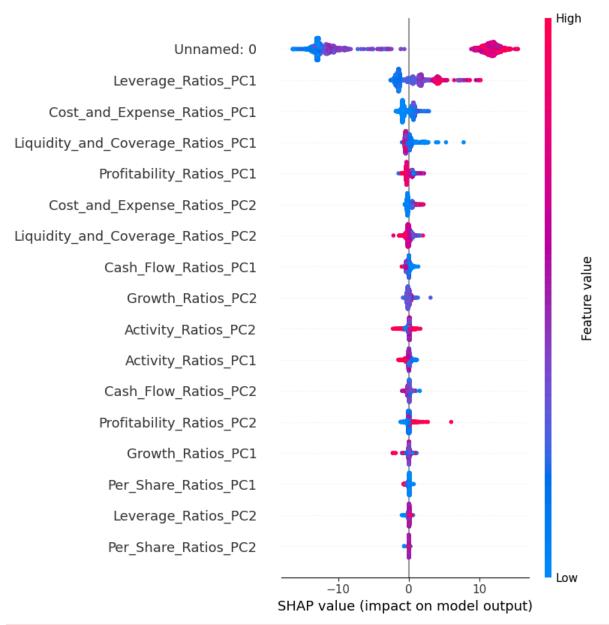
```
2024-06-28 18:15,039 - INFO - LIME explanation for a sample of NaiveBayes created
2024-06-28 18:18:15,039 - WARNING - You are saving your model as an HDF5 file via `model.save()` or `keras.saving.sav
e_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `mod
el.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
2024-06-28 18:18:15,059 - INFO - ANN model saved
2024-06-28 18:18:15,148 - INFO - RandomForest model saved
2024-06-28 18:18:15,156 - INFO - XGBoost model saved
2024-06-28 18:18:15,159 - INFO - SVM model saved
2024-06-28 18:18:15,161 - INFO - LogisticRegression model saved
2024-06-28 18:18:15,188 - INFO - GradientBoosting model saved
2024-06-28 18:18:15,192 - INFO - KNN model saved
2024-06-28 18:18:15,194 - INFO - NaiveBayes model saved
2024-06-28 18:18:15,194 - INFO - Models have been saved
2024-06-28 18:18:15,197 - INFO - {'ANN': {'accuracy': 0.9878260869565217, 'confusion_matrix': array([[1995, 17],
       [ 32, 1981]], dtype=int64), 'f1_score': 0.987783595113438, 'auc_roc': 0.9993836039895747}, 'RandomForest':
{'accuracy': 0.9937888198757764, 'confusion_matrix': array([[2008,
                                                                      4],
       [ 21, 1992]], dtype=int64), 'f1_score': 0.9937640309304066, 'auc_roc': 0.9998035878124201}, 'XGBoost': {'accu
racy': 0.995527950310559, 'confusion_matrix': array([[2005,
                                                              71.
       [ 11, 2002]], dtype=int64), 'f1_score': 0.9955246146195923, 'auc_roc': 0.9998471663807518}, 'SVM': {'accurac
y': 0.9836024844720497, 'confusion_matrix': array([[1986, 26],
       [ 40, 1973]], dtype=int64), 'f1_score': 0.9835493519441675, 'auc_roc': 0.99730800492623}, 'LogisticRegressio
n': {'accuracy': 0.977888198757764, 'confusion_matrix': array([[1971, 41],
       [ 48, 1965]], dtype=int64), 'f1_score': 0.977855187857676, 'auc_roc': 0.9942133093145054}, 'GradientBoostin
g': {'accuracy': 0.9975155279503105, 'confusion_matrix': array([[2012, 0], [ 10, 2003]], dtype=int64), 'f1_score': 0.9975099601593626, 'auc_roc': 0.9999367925581139}, 'KNN': {'accurac
y': 0.9853416149068323, 'confusion_matrix': array([[1978, 34],
       [ 25, 1988]], dtype=int64), 'f1_score': 0.9853779429987608, 'auc_roc': 0.996077681946078}, 'NaiveBayes': {'ac
curacy': 0.564223602484472, 'confusion_matrix': array([[ 317, 1695],
       [ 59, 1954]], dtype=int64), 'f1_score': 0.6902154715648181, 'auc_roc': 0.944120794359526}}
2024-06-28 18:18:15,211 - INFO - Dataset has been split and returned
2024-06-28 18:18:15,223 - INFO - Data has been standardized
2024-06-28 18:20:14,168 - INFO - ANN has been trained in 118.95 seconds
2024-06-28 18:27:42,607 - INFO - RandomForest has been trained in 448.44 seconds
2024-06-28 18:27:53,366 - INFO - XGBoost has been trained in 10.76 seconds
2024-06-28 18:29:58,901 - INFO - SVM has been trained in 125.53 seconds
2024-06-28 18:29:59,247 - INFO - LogisticRegression has been trained in 0.35 seconds
2024-06-28 20:41:58,820 - INFO - GradientBoosting has been trained in 7919.57 seconds
2024-06-28 20:42:07,660 - INFO - KNN has been trained in 8.84 seconds
2024-06-28 20:42:07,688 - INFO - Naive Bayes has been trained in 0.03 seconds
126/126
                            - 1s 5ms/step
2024-06-28 20:42:11,334 - INFO - Models have been tested in 3.64 seconds
126/126
                           - 1s 4ms/step
2024-06-28 20:42:15,153 - INFO - Models have been evaluated in 3.82 seconds
```



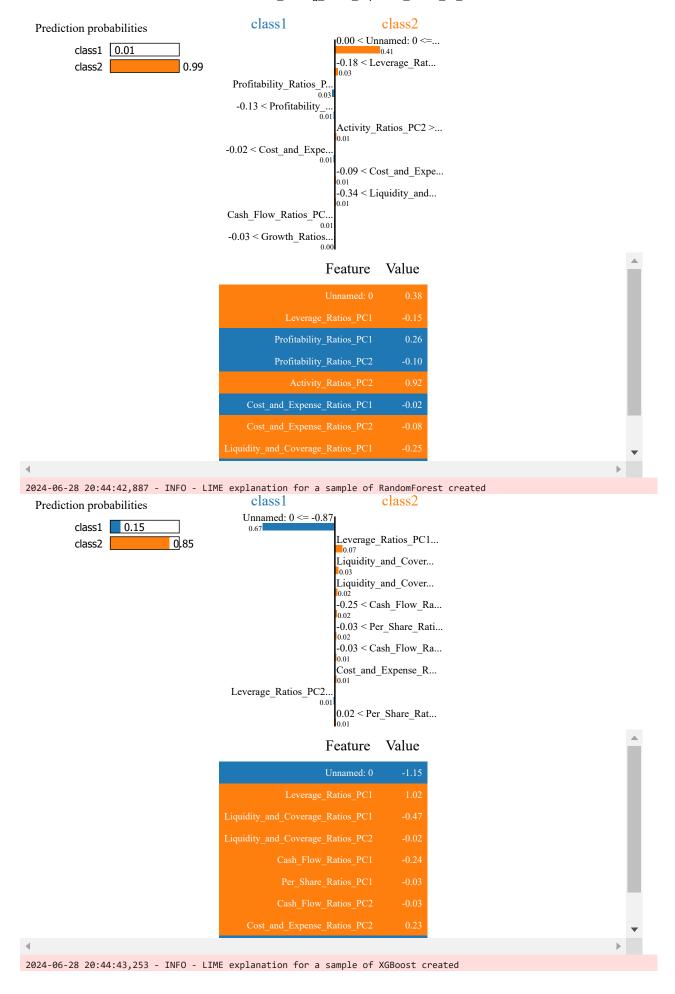
2024-06-28 20:43:41,903 - INFO - SHAP summary plot for RandomForest created

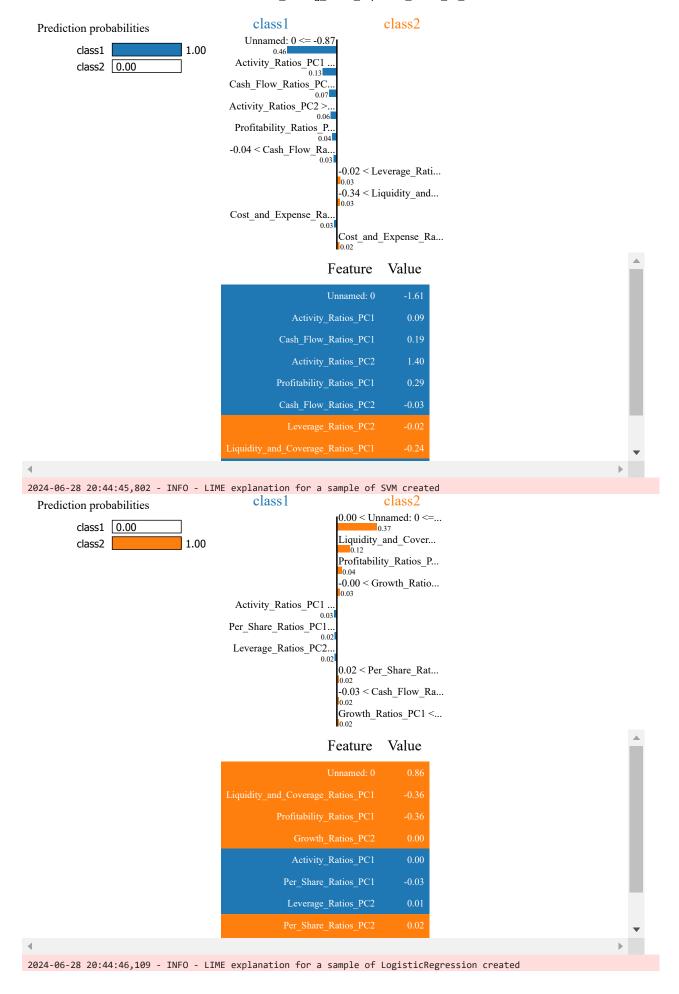


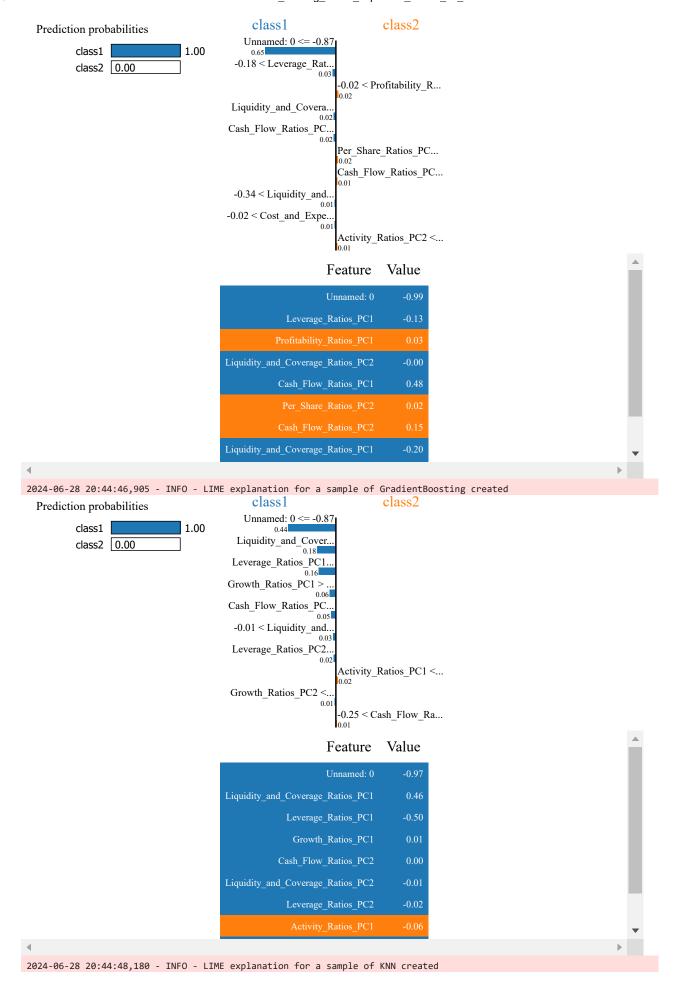
2024-06-28 20:43:47,904 - INFO - SHAP summary plot for XGBoost created
2024-06-28 20:43:47,907 - ERROR - Error generating SHAP explanations for SVM: Model type not yet supported by TreeExp lainer: <class 'sklearn.svm._classes.SVC'>
2024-06-28 20:43:47,909 - ERROR - Error generating SHAP explanations for LogisticRegression: Model type not yet supported by TreeExplainer: <class 'sklearn.linear_model._logistic.LogisticRegression'>

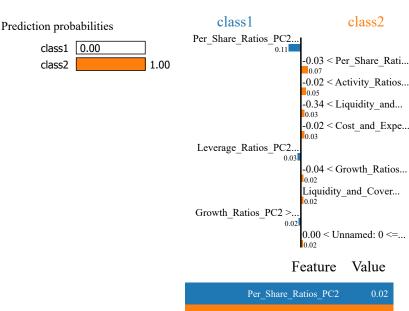


2024-06-28 20:44:41,998 - INFO - SHAP summary plot for GradientBoosting created
2024-06-28 20:44:42,001 - ERROR - Error generating SHAP explanations for KNN: Model type not yet supported by TreeExp lainer: <class 'sklearn.neighbors._classification.KNeighborsClassifier'>
2024-06-28 20:44:42,004 - ERROR - Error generating SHAP explanations for NaiveBayes: Model type not yet supported by TreeExplainer: <class 'sklearn.naive_bayes.GaussianNB'>









Per_Share_Ratios_PC2 0.02

Per_Share_Ratios_PC1 -0.03

Activity_Ratios_PC1 -0.01

Liquidity_and_Coverage_Ratios_PC1 -0.25

Cost_and_Expense_Ratios_PC1 -0.02

Leverage_Ratios_PC2 0.04

Growth_Ratios_PC1 -0.04

Liquidity_and_Coverage_Ratios_PC2 -0.03

```
2024-06-28 20:44:48,481 - INFO - LIME explanation for a sample of NaiveBayes created
2024-06-28 20:44:48,485 - WARNING - You are saving your model as an HDF5 file via `model.save()` or `keras.saving.sav
e_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `mod
el.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
2024-06-28 20:44:48,613 - INFO - ANN model saved
2024-06-28 20:44:48,861 - INFO - RandomForest model saved
2024-06-28 20:44:48,901 - INFO - XGBoost model saved
2024-06-28 20:44:48,913 - INFO - SVM model saved
2024-06-28 20:44:48,922 - INFO - LogisticRegression model saved
2024-06-28 20:44:49,080 - INFO - GradientBoosting model saved
2024-06-28 20:44:49,096 - INFO - KNN model saved
2024-06-28 20:44:49,106 - INFO - NaiveBayes model saved
2024-06-28 20:44:49,108 - INFO - Models have been saved
2024-06-28 20:44:49,117 - INFO - {'ANN': {'accuracy': 0.986832298136646, 'confusion_matrix': array([[1982, 30],
       [ 23, 1990]], dtype=int64), 'f1_score': 0.9868584180510787, 'auc_roc': 0.9982137725065405}, 'RandomForest':
{'accuracy': 0.9935403726708074, 'confusion_matrix': array([[2007,
                                                                     5],
       [ 21, 1992]], dtype=int64), 'f1_score': 0.9935162094763093, 'auc_roc': 0.9997444542876868}, 'XGBoost': {'accu
racy': 0.995527950310559, 'confusion_matrix': array([[2005,
                                                              7],
       [ 11, 2002]], dtype=int64), 'f1_score': 0.9955246146195923, 'auc_roc': 0.9998471663807518}, 'SVM': {'accurac
y': 0.9836024844720497, 'confusion_matrix': array([[1986, 26],
       [ 40, 1973]], dtype=int64), 'f1_score': 0.9835493519441675, 'auc_roc': 0.99730800492623}, 'LogisticRegressio
n': {'accuracy': 0.977888198757764, 'confusion_matrix': array([[1971, 41],
       [ 48, 1965]], dtype=int64), 'f1_score': 0.977855187857676, 'auc_roc': 0.9942133093145054}, 'GradientBoostin
g': {'accuracy': 0.9970186335403727, 'confusion_matrix': array([[2010,
                                                                        2],
       [ 10, 2003]], dtype=int64), 'f1_score': 0.9970134395221503, 'auc_roc': 0.9999017321801926}, 'KNN': {'accurac
y': 0.9853416149068323, 'confusion_matrix': array([[1978, 34],
       [ 25, 1988]], dtype=int64), 'f1_score': 0.9853779429987608, 'auc_roc': 0.996077681946078}, 'NaiveBayes': {'ac
curacy': 0.564223602484472, 'confusion_matrix': array([[ 317, 1695],
       [ 59, 1954]], dtype=int64), 'f1_score': 0.6902154715648181, 'auc_roc': 0.944120794359526}}
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Results for df mice
{'ANN': {'accuracy': 0.9878260869565217, 'confusion_matrix': array([[1995, 17],
      [ 32, 1981]], dtype=int64), 'f1_score': 0.987783595113438, 'auc_roc': 0.9993836039895747}, 'RandomForest':
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{'accuracy': 0.9937888198757764, 'confusion matrix': array([[2008,
      [ 21, 1992]], dtype=int64), 'f1 score': 0.9937640309304066, 'auc roc': 0.9998035878124201}, 'XGBoost': {'accu
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      [ 40, 1973]], dtype=int64), 'f1_score': 0.9835493519441675, 'auc_roc': 0.99730800492623}, 'LogisticRegressio
g': {'accuracy': 0.9975155279503105, 'confusion_matrix': array([[2012,
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Results for df AE
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      [ 10, 2003]], dtype=int64), 'f1_score': 0.9970134395221503, 'auc_roc': 0.9999017321801926}, 'KNN': {'accurac
y': 0.9853416149068323, 'confusion_matrix': array([[1978, 34],
      [ 25, 1988]], dtype=int64), 'f1_score': 0.9853779429987608, 'auc_roc': 0.996077681946078}, 'NaiveBayes': {'ac
curacy': 0.564223602484472, 'confusion matrix': array([[ 317, 1695],
      [ 59, 1954]], dtype=int64), 'f1_score': 0.6902154715648181, 'auc_roc': 0.944120794359526}}
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