Machine Learning Approaches for Predicting Coronary Heart Disease

Dataset

In [31]:
```
import pandas as pd

# Load the dataset
data = pd.read_csv('/Users/nick/Downloads/heart-disease.csv')

# Display first few rows
data.head()
```

Out[31]:

	sbp	tobacco	ldl	adiposity	famhist	typea	obesity	alcohol	age	chd
0	160	12.00	5.73	23.11	Present	49	25.30	97.20	52	1
1	144	0.01	4.41	28.61	Absent	55	28.87	2.06	63	1
2	118	0.08	3.48	32.28	Present	52	29.14	3.81	46	0
3	170	7.50	6.41	38.03	Present	51	31.99	24.26	58	1
4	134	13.60	3.50	27.78	Present	60	25.99	57.34	49	1

Data Pre-processing

In [32]:
```
import pandas as pd

# Check and encode 'famhist' column
if 'famhist' in data.columns:
    # Map 'Present' to 1 and 'Absent' to 0
    data['Famhist'] = data['famhist'].map({'Present': 1, 'Absent': 0})
    # Remove original 'famhist' column
    data.drop('famhist', axis=1, inplace=True)
else:
    # Check for missing values
    print("'famhist' column does not exist in the DataFrame.")

# Identify any missing values across columns
missing_values = data.isnull().sum()
print(missing_values)

# Save the cleaned data to a new CSV file
data.to_csv('/Users/nick/Downloads/preprocessed_data.csv', index=False)
# Confirmation message
print('Preprocessed data has been saved.')

# Show the first few rows to confirm changes
data.head()
```

```
sbp          0
tobacco      0
ldl          0
adiposity    0
typea        0
obesity      0
alcohol      0
age          0
chd          0
Famhist      0
dtype: int64
Preprocessed data has been saved.
```

Out[32]:

	sbp	tobacco	ldl	adiposity	typea	obesity	alcohol	age	chd	Famhist
0	160	12.00	5.73	23.11	49	25.30	97.20	52	1	1
1	144	0.01	4.41	28.61	55	28.87	2.06	63	1	0
2	118	0.08	3.48	32.28	52	29.14	3.81	46	0	1
3	170	7.50	6.41	38.03	51	31.99	24.26	58	1	1
4	134	13.60	3.50	27.78	60	25.99	57.34	49	1	1

Exploratory Data Analysis (EDA)

Descriptive Statistics

In [33]:
```
import pandas as pd

# Calculate statistical characteristics of the dataset
statistical_characteristics = data.describe()
```

```
# Display the statistical characteristics
statistical_characteristics
```

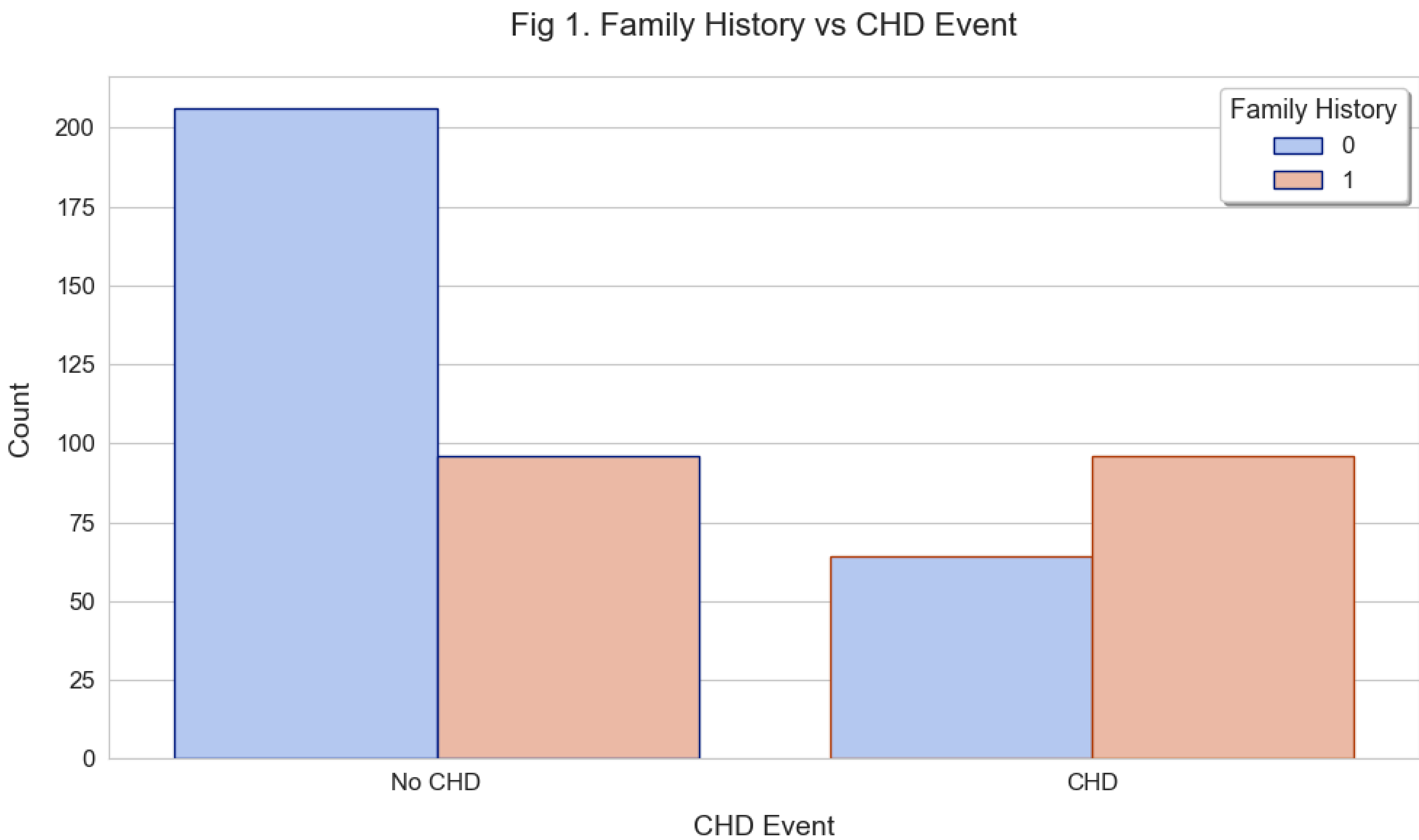
Out[33]:

	sbp	tobacco	ldl	adiposity	typea	obesity	alcohol	age	chd	Famhist
count	462.000000	462.000000	462.000000	462.000000	462.000000	462.000000	462.000000	462.000000	462.000000	462.000000
mean	138.326840	3.635649	4.740325	25.406732	53.103896	26.044113	17.044394	42.816017	0.346320	0.415584
std	20.496317	4.593024	2.070909	7.780699	9.817534	4.213680	24.481059	14.608956	0.476313	0.493357
min	101.000000	0.000000	0.980000	6.740000	13.000000	14.700000	0.000000	15.000000	0.000000	0.000000
25%	124.000000	0.052500	3.282500	19.775000	47.000000	22.985000	0.510000	31.000000	0.000000	0.000000
50%	134.000000	2.000000	4.340000	26.115000	53.000000	25.805000	7.510000	45.000000	0.000000	0.000000
75%	148.000000	5.500000	5.790000	31.227500	60.000000	28.497500	23.892500	55.000000	1.000000	1.000000
max	218.000000	31.200000	15.330000	42.490000	78.000000	46.580000	147.190000	64.000000	1.000000	1.000000

Family History and CHD Events

In [34]:

```python
import matplotlib.pyplot as plt
import seaborn as sns


# Create a more attractive countplot with seaborn
plt.figure(figsize=(10, 6))
sns.set_style("whitegrid")
sns.countplot(x='chd', hue='Famhist', data=data, palette='coolwarm', edgecolor=sns.color_palette("dark", 3))

# Add labels, title, and improve legend
plt.xlabel('CHD Event', fontsize=14, labelpad=10)
plt.ylabel('Count', fontsize=14, labelpad=10)
plt.title('Fig 1. Family History vs CHD Event', fontsize=16, pad=20)
plt.xticks([0, 1], ['No CHD', 'CHD'], fontsize=12)
plt.yticks(fontsize=12)
plt.legend(title='Family History', title_fontsize='13', fontsize='12', loc='upper right', frameon=True, shadow=True)

# Show the plot
plt.tight_layout()
plt.show()
```

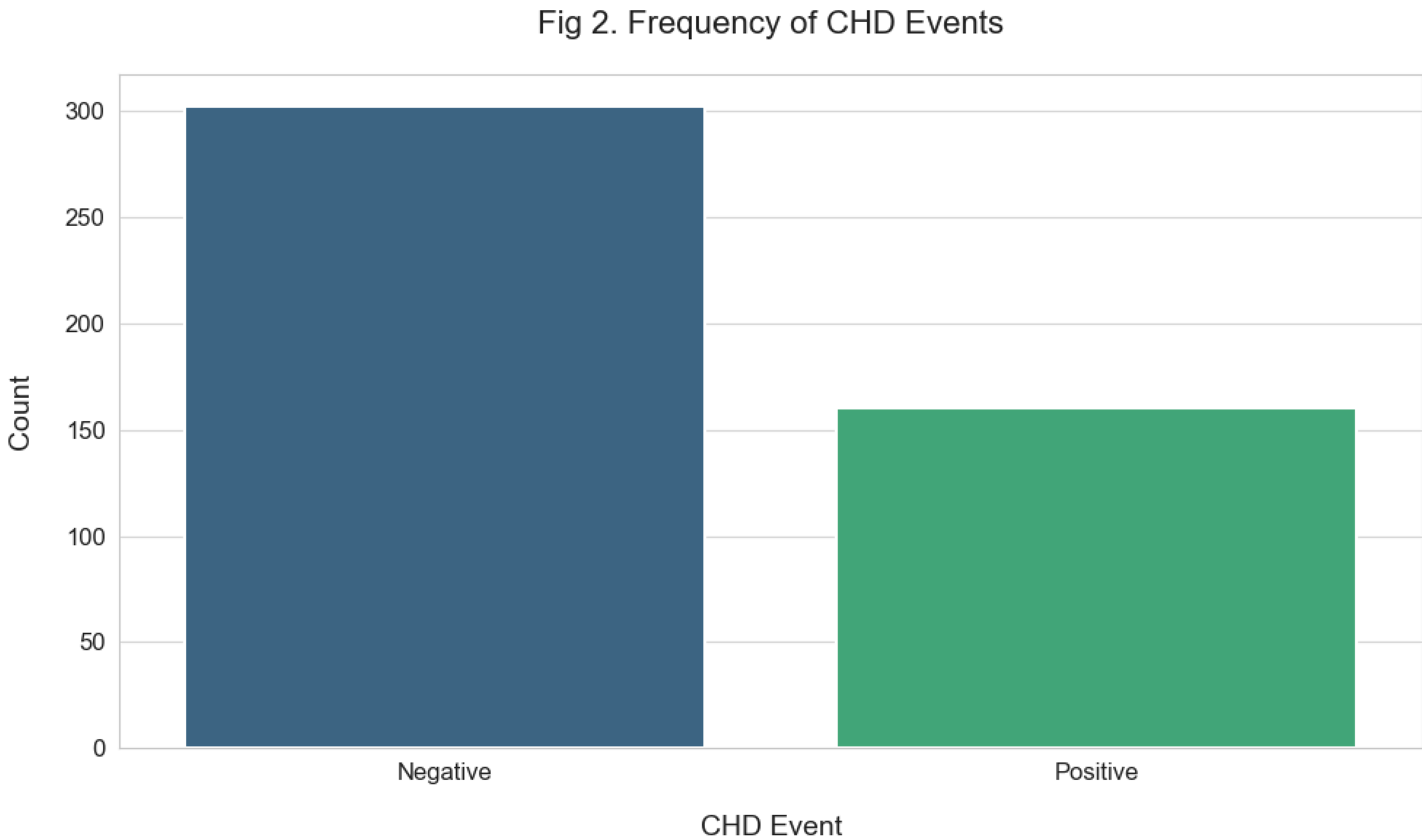


CHD Event Frequency

In [35]:

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Set the aesthetic style of the plots
sns.set_style("whitegrid")

# Create a more attractive countplot with seaborn
```

```
plt.figure(figsize=(10, 6))
sns.countplot(x='chd', data=data, palette='viridis', saturation=0.75,linewidth=1.5)

# Add labels, title, and improve font sizes
plt.xlabel('CHD Event', fontsize=14, labelpad=15)
plt.ylabel('Count', fontsize=14, labelpad=15)
plt.title('Fig 2. Frequency of CHD Events', fontsize=16, pad=20)
plt.xticks([0, 1], ['Negative', 'Positive'], fontsize=12)
plt.yticks(fontsize=12)

# Adding gridlines for better readability
plt.grid(axis='y', linestyle='-', alpha=0.7)

# Ensure layout is well-organized
plt.tight_layout()

# Show the plot
plt.show()
```



Data Imbalance

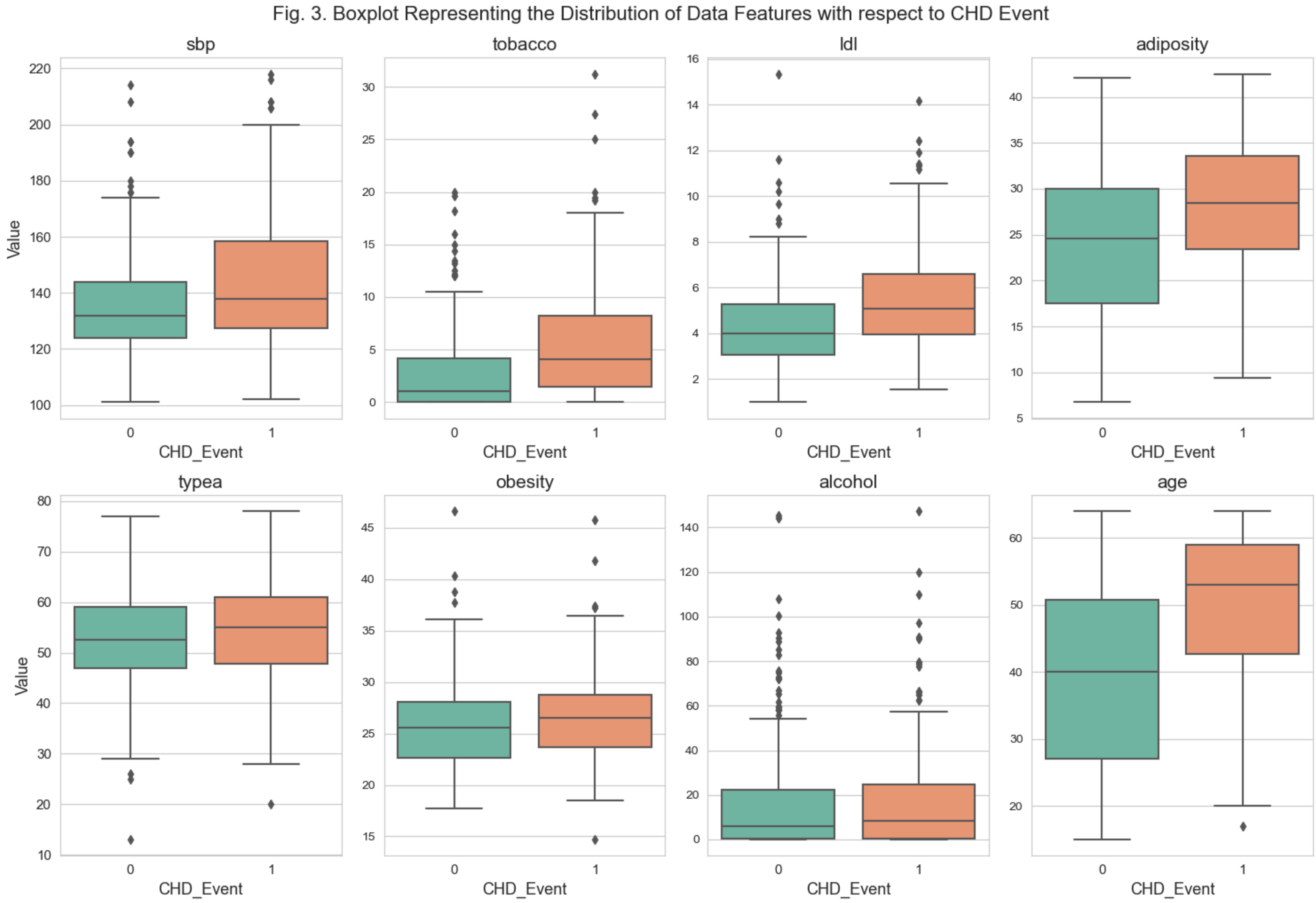
In [36]:
```
import pandas as pd

# 'chd' is the target column
y = data['chd']

# Count the occurrences of each class in the target column
class_distribution = y.value_counts()

# Calculate the percentage of each class
class_percentage = y.value_counts(normalize=True) * 100

print("Class Distribution:\n", class_distribution)
print("\nClass Percentage:\n", class_percentage)
```

```
Class Distribution:
 chd
0    302
1    160
Name: count, dtype: int64

Class Percentage:
 chd
0    65.367965
1    34.632035
Name: proportion, dtype: float64
```

Boxplot Analysis

In [37]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# Define figure size and layout
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(15, 10))

# Flatten axes for iteration
axes = axes.flatten()

# Features to plot
features = ['sbp', 'tobacco', 'ldl', 'adiposity', 'typea', 'obesity', 'alcohol', 'age']

# Create boxplot for each feature
for i, feature in enumerate(features):
    # Plot boxplot
    sns.boxplot(data=data, x='chd', y=feature, ax=axes[i], palette="Set2")

    # Set subplot title
    axes[i].set_title(feature, fontsize=15)

    # Set x-axis label and increase font size
    axes[i].set_xlabel('CHD_Event', fontsize=13)
    axes[i].tick_params(axis='x', labelsize=11)

    if i % 4 == 0:
        # Set y-axis label and increase font size for the first column
        axes[i].set_ylabel('Value', fontsize=13)
        axes[i].tick_params(axis='y', labelsize=11)
    else:
        # Clear y-axis label to avoid clutter
        axes[i].set_ylabel('')

# Adjust layout
plt.tight_layout()

# Set main title
plt.suptitle('Fig. 3. Boxplot Representing the Distribution of Data Features with respect to CHD Event',
             fontsize=16, y=1.02)

# Show plot
plt.show()
```

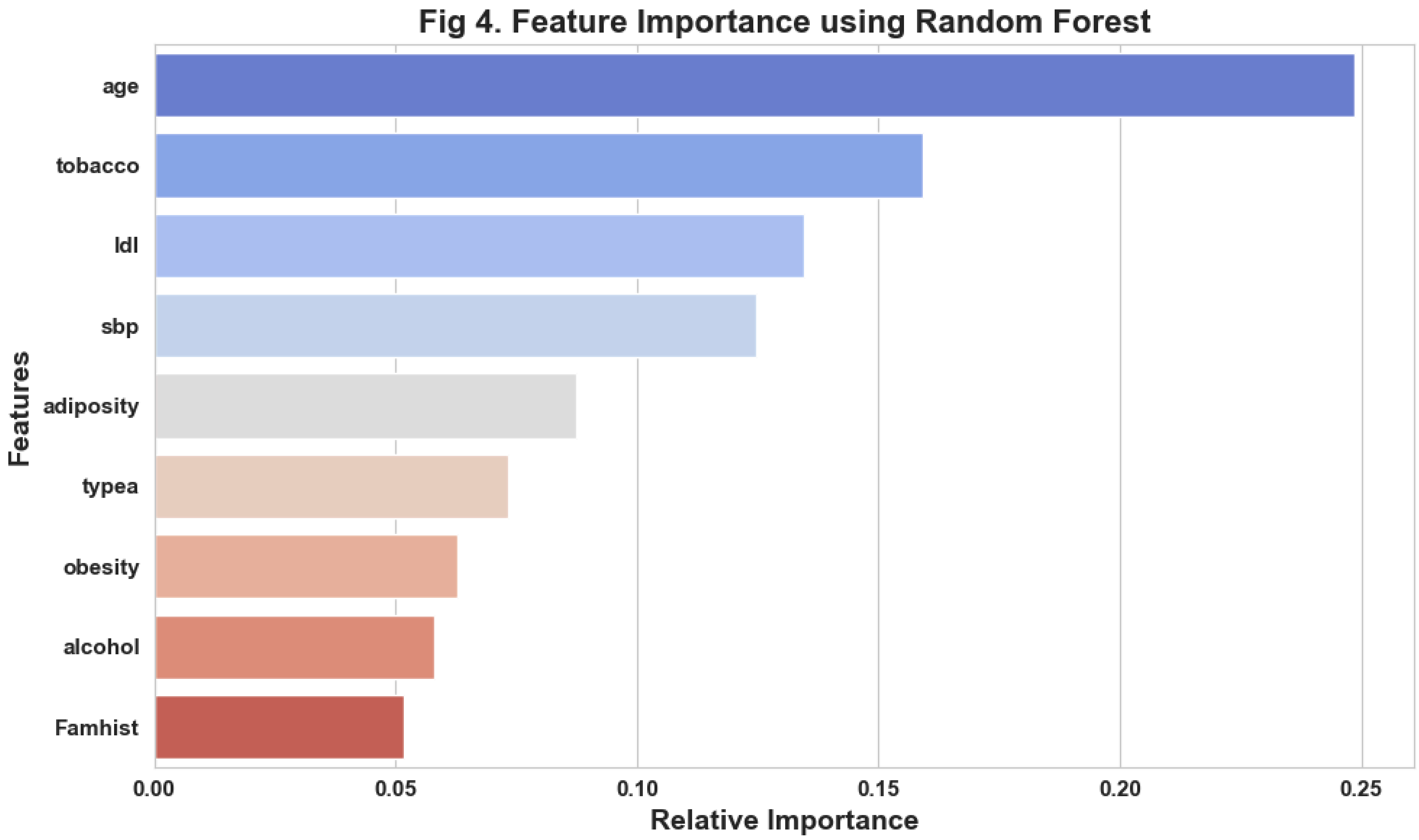


Features importance using Random Forest

In [38]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```python
from imblearn.over_sampling import KMeansSMOTE
from imblearn.pipeline import make_pipeline as make_pipeline_imb
import matplotlib.pyplot as plt
import seaborn as sns

# Load the preprocessed dataset
df = pd.read_csv('/Users/nick/Downloads/preprocessed_data.csv')

# Prepare the features (X) and target (y)
X = df.drop('chd', axis=1)
y = df['chd']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Pipeline setup with SMOTE and RandomForestClassifier
pipeline = make_pipeline_imb(
    StandardScaler(),
    KMeansSMOTE(random_state=42),
    RandomForestClassifier(random_state=42)
)

# Define grid search parameters
param_grid = {
    'randomforestclassifier__n_estimators': [100, 500, 600],
    'randomforestclassifier__max_depth': [None, 10, 20, 30],
    'randomforestclassifier__min_samples_split': [2, 5, 10],
    'randomforestclassifier__min_samples_leaf': [1, 2, 4]
}

# Initialize GridSearchCV
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', verbose=1, n_jobs=-1)

# Fit the model on the training data
grid_search.fit(X_train, y_train)

# Best model from grid search
best_model = grid_search.best_estimator_

# Predict on the test set using the best model
y_pred = best_model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Get feature importances from the best model
feature_importances = best_model.named_steps['randomforestclassifier'].feature_importances_

# Create a pandas Series with feature names and their importance scores
importances = pd.Series(feature_importances, index=X.columns)

# Sort the feature importances in descending order
sorted_importances = importances.sort_values(ascending=False)

# Create a horizontal bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x=sorted_importances, y=sorted_importances.index, palette='coolwarm')

# Add labels and title to the plot
plt.xlabel('Relative Importance', fontsize=14, weight='bold')
plt.ylabel('Features', fontsize=14, weight='bold')
plt.title('Fig 4. Feature Importance using Random Forest', fontsize=16, weight='bold')
plt.xticks(fontsize=11, ha='center', weight='bold')
plt.yticks(fontsize=11, weight='bold')

# Show the plot
plt.tight_layout()
plt.show()
```

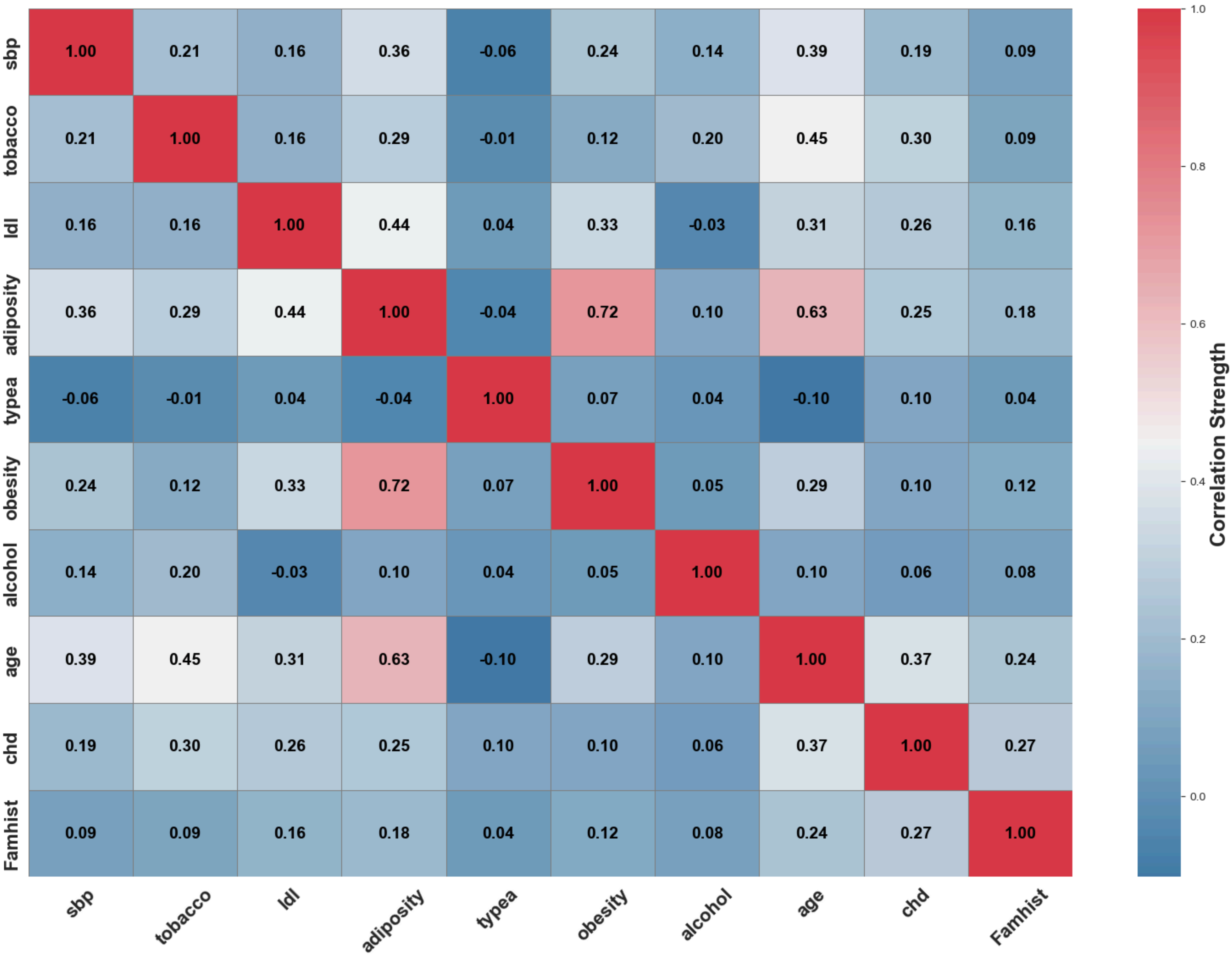
```
Fitting 10 folds for each of 108 candidates, totalling 1080 fits
Accuracy: 0.7419354838709677
```



Correlation Analysis

In [39]:
```
# Compute correlation matrix
correlation_matrix = df.corr()

# Choose a seaborn style with whitegrid but without the internal grid
sns.set_style('whitegrid', {'axes.grid': False})

# Set up a larger figure size for better readability
plt.figure(figsize=(16, 12))

# Create a diverging color palette for better distinction of values
cmap = sns.diverging_palette(240, 10, n=9, as_cmap=True)

# Generating a heatmap with annotations, a float format, and our color map
ax = sns.heatmap(correlation_matrix,
                 annot=True,
                 cmap=cmap,
                 fmt=".2f",
                 annot_kws={"size": 14, "weight": "bold", "color": "black"},
                 linewidths=0.5,  # Reduce line width for minimal style
                 linecolor='gray',  # Neutral line color
                 cbar_kws={'shrink': 1, 'label': 'Correlation Strength'})

# Increasing font size for correlation strength in colorbar and making it bold
cbar = ax.collections[0].colorbar
cbar.ax.set_ylabel('Correlation Strength', fontsize=18, weight='bold')

# Title and labels
plt.title('Fig 5. Pearson Correlation Coefficient Matrix', fontsize=24, pad=20, weight='bold')
plt.xticks(fontsize=16, rotation=45, ha='center', weight='bold')
plt.yticks(fontsize=16, weight='bold')

# Tight layout for spacing
plt.tight_layout()

# Show plot
plt.show()
```

Fig 5. Pearson Correlation Coefficient Matrix



Logistic Regression with Ridge Penalty

In [40]:
```python
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from imblearn.over_sampling import SMOTE, KMeansSMOTE, SVMSMOTE
from imblearn.pipeline import Pipeline as ImbPipeline

# Setup features and target, excluding 'obesity'
X = df.drop(['chd', 'obesity'], axis=1)
y = df['chd']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Setup pipeline with scaling, SMOTE, and logistic regression
pipeline = ImbPipeline([
    ('scaler', StandardScaler()),
    ('kmeanssmote', KMeansSMOTE(random_state=42)),
    ('logisticregression', LogisticRegression(random_state=42, max_iter=10000))
])

# Define hyperparameter space
param_grid = {
    'logisticregression__C': [0.001, 0.01, 0.1, 0.25, 0.5, 1, 10, 100],
    'logisticregression__solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
    'logisticregression__penalty': ['l2']
}

# Grid search for best parameters
grid_search = GridSearchCV(pipeline, param_grid, scoring='accuracy', cv=10, verbose=1)
grid_search.fit(X_train, y_train)

# Output best parameters and CV score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")
```

```
# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Evaluate on test set
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Calculate and print specificity
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
Best parameters: {'logisticregression__C': 0.01, 'logisticregression__penalty': 'l2', 'logisticregression__solver': 'newton-c
g'}
Best CV score: 0.7075
Accuracy: 0.7527
F1 Score: 0.7557
Precision: 0.7630
Recall: 0.7527
Specificity: 0.7627
```

Classifier Exploration

Support Vector Machine (SVM)

In [41]:

```
# Import necessary libraries
from sklearn.svm import SVC

# Create pipeline: scaling, SMOTE, SVM classifier
pipeline = ImbPipeline([
    ('scaler', StandardScaler()),
    ('svmsmote', SVMSMOTE(random_state=42, k_neighbors=5, m_neighbors=10)),
    ('svm', SVC(random_state=42))])

# Define grid search parameters
param_grid = {
    'svm__kernel': ['rbf'],
    'svm__C': [8, 10, 12, 14, 16],
    'svm__gamma': [0.01, 0.05, 0.1, 0.15, 0.2]}

# Execute grid search
grid_search = GridSearchCV(pipeline, param_grid, scoring='accuracy', cv=10, verbose=1)
grid_search.fit(X_train, y_train)

# Output best model details
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Test model performance
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity from confusion matrix
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 25 candidates, totalling 250 fits
Best parameters: {'svm__C': 14, 'svm__gamma': 0.01, 'svm__kernel': 'rbf'}
Best CV score: 0.6968
Accuracy: 0.7849
F1 Score: 0.7835
Precision: 0.7828
Recall: 0.7849
Specificity: 0.8475
```

K-Nearest Neighbours (KNN)

In [42]:

```
# Import necessary libraries
from sklearn.neighbors import KNeighborsClassifier

# Pipeline: Scale data, apply SMOTE, use KNN
pipeline = ImbPipeline([
    ('scaler', StandardScaler()),
    ('kmeanssmote', KMeansSMOTE(random_state=42)),
    ('knn', KNeighborsClassifier())])

# Hyperparameters for grid search
param_grid = {
```

```
    'knn__n_neighbors': [5, 10, 15, 18, 20, 21, 22, 23, 24, 25],
    'knn__metric': ['minkowski', 'euclidean', 'manhattan'],
    'knn__p': [1, 2]}

# Execute grid search
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', verbose=1)
grid_search.fit(X_train, y_train)

# Output best model details
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test model on hold-out set
y_pred = grid_search.best_estimator_.predict(X_test)

# Print performance metrics
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity from confusion matrix
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 60 candidates, totalling 600 fits
Best parameters: {'knn__metric': 'minkowski', 'knn__n_neighbors': 21, 'knn__p': 2}
Best CV score: 0.7128
Accuracy: 0.7419
F1 Score: 0.7419
Precision: 0.7419
Recall: 0.7419
Specificity: 0.7966
```

Multilayer Perceptron (MLP) Neural Network

In [43]:

```
# Import necessary libraries
from sklearn.neural_network import MLPClassifier

# Pipeline: Scale data, apply SMOTE, use MLP classifier
pipeline = ImbPipeline([
    ('scaler', StandardScaler()),
    ('kmeanssmote', KMeansSMOTE(random_state=42)),
    ('mlpclassifier', MLPClassifier(random_state=42, max_iter=1000))])

# Define grid search parameters
param_grid = {
    'mlpclassifier__hidden_layer_sizes': [(100,), (100, 50), (128, 64)],
    'mlpclassifier__activation': ['tanh', 'relu'],
    'mlpclassifier__solver': ['sgd', 'adam'],
    'mlpclassifier__learning_rate_init': [0.001, 0.01],
    'mlpclassifier__alpha': [0.0001, 0.001],
    'mlpclassifier__early_stopping': [True]}

# Execute grid search
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', verbose=1)
grid_search.fit(X_train, y_train)  # Fit model

# Output best model details
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Test model performance
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity from confusion matrix
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 48 candidates, totalling 480 fits
Best parameters: {'mlpclassifier__activation': 'relu', 'mlpclassifier__alpha': 0.0001, 'mlpclassifier__early_stopping': True,
'mlpclassifier__hidden_layer_sizes': (128, 64), 'mlpclassifier__learning_rate_init': 0.01, 'mlpclassifier__solver': 'sgd'}
Best CV score: 0.7047
Accuracy: 0.7634
F1 Score: 0.7667
Precision: 0.7763
Recall: 0.7634
Specificity: 0.7627
```

Naive Bayes

In [44]:

```
# Import necessary libraries
from sklearn.preprocessing import Binarizer
from sklearn.naive_bayes import BernoulliNB

# Pipeline: Binarizer + SMOTE + BernoulliNB
pipeline = make_pipeline_imb(
    Binarizer(),
    SMOTE(random_state=42),
    BernoulliNB())

# Parameters for grid search
param_grid = {
    'binarizer__threshold': [0.15, 0.175, 0.2, 0.225, 0.25],
    'bernoullinb__alpha': [0.0005, 0.00075, 0.001, 0.00125, 0.0015],
    'bernoullinb__class_prior': [
        [0.55, 0.45], [0.575, 0.425],
        [0.6, 0.4],
        [0.625, 0.375], [0.65, 0.35]]}

# Execute grid search
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', verbose=1)
grid_search.fit(X_train, y_train)

# Display best parameters and score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Model evaluation on test set
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity from confusion matrix
cm = confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = cm.ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 125 candidates, totalling 1250 fits
Best parameters: {'bernoullinb__alpha': 0.0005, 'bernoullinb__class_prior': [0.55, 0.45], 'binarizer__threshold': 0.15}
Best CV score: 0.6992
Accuracy: 0.7204
F1 Score: 0.7185
Precision: 0.7173
Recall: 0.7204
Specificity: 0.7966
```

Quadratic Discriminant Analysis (QDA)

In [45]:

```
# Import necessary libraries
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

# Pipeline setup: Scale -> SMOTE -> QDA
pipeline = make_pipeline_imb(
    StandardScaler(),
    KMeansSMOTE(random_state=42),
    QuadraticDiscriminantAnalysis())

# Grid search parameters
param_grid = {
    'quadraticdiscriminantanalysis__reg_param': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]}

# Execute grid search
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', n_jobs=-1, verbose=1)
grid_search.fit(X_train, y_train)

# Output best hyperparameters
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Evaluate on test set
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity calculation
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 13 candidates, totalling 130 fits
Best parameters: {'quadraticdiscriminantanalysis__reg_param': 0.25}
Best CV score: 0.7209
Accuracy: 0.7957
F1 Score: 0.7974
Precision: 0.8007
Recall: 0.7957
Specificity: 0.8136
```

Linear Discriminant Analysis (LDA)

In [46]:

```python
# Import necessary libraries
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

# Pipeline: Scale -> Balance (SMOTE) -> Classify (LDA)
pipeline = make_pipeline_imb(
    StandardScaler(),
    SMOTE(random_state=42),
    LinearDiscriminantAnalysis())

# Define hyperparameters for GridSearch
param_grid = {
    'lineardiscriminantanalysis__solver': ['lsqr', 'eigen'],
    'lineardiscriminantanalysis__shrinkage': [0.85, 0.875, 0.9, 0.925, 0.95],}

# GridSearch for optimal parameters
grid_search = GridSearchCV(pipeline, param_grid, cv=10, scoring='accuracy', verbose=1)
grid_search.fit(X_train, y_train)

# Display best parameters/score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV score: {grid_search.best_score_:.4f}")

# Test set predictions
y_pred = grid_search.best_estimator_.predict(X_test)

# Evaluate on test set
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Precision: {precision_score(y_test, y_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, y_pred, average='weighted'):.4f}")

# Specificity calculation
tn, fp, _, _ = confusion_matrix(y_test, y_pred).ravel()
specificity = tn / (tn + fp)
print(f"Specificity: {specificity:.4f}")
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Best parameters: {'lineardiscriminantanalysis__shrinkage': 0.925, 'lineardiscriminantanalysis__solver': 'lsqr'}
Best CV score: 0.6885
Accuracy: 0.7097
F1 Score: 0.7150
Precision: 0.7479
Recall: 0.7097
Specificity: 0.6610
```

In [ ]: