heart-attack-prediction-1

February 12, 2025

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
from imblearn.over_sampling import SMOTE
```

[4]:
```
df = pd.read_csv('heart_disease.csv')
```

[5]:
```
df.head()
```

[5]:
```
    Age  Gender  Blood Pressure  Cholesterol Level Exercise Habits Smoking  \
0  56.0    Male           153.0              155.0            High     Yes
1  69.0  Female           146.0              286.0            High      No
2  46.0    Male           126.0              216.0             Low      No
3  32.0  Female           122.0              293.0            High     Yes
4  60.0    Male           166.0              242.0             Low     Yes

  Family Heart Disease Diabetes        BMI High Blood Pressure  …  \
0                  Yes       No  24.991591                 Yes  …
1                  Yes      Yes  25.221799                  No  …
2                   No       No  29.855447                  No  …
3                  Yes       No  24.130477                 Yes  …
4                  Yes      Yes  20.486289                 Yes  …

  High LDL Cholesterol Alcohol Consumption Stress Level Sleep Hours  \
0                   No                High       Medium    7.633228
1                   No              Medium         High    8.744034
2                  Yes                 Low          Low    4.440440
3                  Yes                 Low         High    5.249405
4                   No                 Low         High    7.030971

   Sugar Consumption Triglyceride Level  Fasting Blood Sugar  CRP Level  \
0             Medium              342.0                  NaN  12.969246
```

```
1             Medium              133.0                 157.0   9.355389
2                Low              393.0                  92.0  12.709873
3               High              293.0                  94.0  12.509046
4               High              263.0                 154.0  10.381259

   Homocysteine Level  Heart Disease Status
0           12.387250                    No
1           19.298875                    No
2           11.230926                    No
3            5.961958                    No
4            8.153887                    No

[5 rows x 21 columns]
```

[7]:
```python
print(df.shape)
```

```
(10000, 21)
```

[10]:
```python
print(df.dtypes)
```

```
Age                     float64
Gender                   object
Blood Pressure          float64
Cholesterol Level       float64
Exercise Habits          object
Smoking                  object
Family Heart Disease     object
Diabetes                 object
BMI                     float64
High Blood Pressure      object
Low HDL Cholesterol      object
High LDL Cholesterol     object
Alcohol Consumption      object
Stress Level             object
Sleep Hours             float64
Sugar Consumption        object
Triglyceride Level      float64
Fasting Blood Sugar     float64
CRP Level               float64
Homocysteine Level      float64
Heart Disease Status     object
dtype: object
```

[11]:
```python
df.describe()
```

[11]:
```
               Age  Blood Pressure  Cholesterol Level          BMI  \
count  9971.000000     9981.000000        9970.000000  9978.000000
```

```
mean     49.296259    149.757740         225.425577    29.077269
std      18.193970     17.572969          43.575809     6.307098
min      18.000000    120.000000         150.000000    18.002837
25%      34.000000    134.000000         187.000000    23.658075
50%      49.000000    150.000000         226.000000    29.079492
75%      65.000000    165.000000         263.000000    34.520015
max      80.000000    180.000000         300.000000    39.996954

       Sleep Hours  Triglyceride Level  Fasting Blood Sugar    CRP Level  \
count  9975.000000         9974.000000          9978.000000  9974.000000
mean      6.991329          250.734409           120.142213     7.472201
std       1.753195           87.067226            23.584011     4.340248
min       4.000605          100.000000            80.000000     0.003647
25%       5.449866          176.000000            99.000000     3.674126
50%       7.003252          250.000000           120.000000     7.472164
75%       8.531577          326.000000           141.000000    11.255592
max       9.999952          400.000000           160.000000    14.997087

       Homocysteine Level
count         9980.000000
mean            12.456271
std              4.323426
min              5.000236
25%              8.723334
50%             12.409395
75%             16.140564
max             19.999037
```

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Age                   9971 non-null   float64
 1   Gender                9981 non-null   object
 2   Blood Pressure        9981 non-null   float64
 3   Cholesterol Level     9970 non-null   float64
 4   Exercise Habits       9975 non-null   object
 5   Smoking               9975 non-null   object
 6   Family Heart Disease  9979 non-null   object
 7   Diabetes              9970 non-null   object
 8   BMI                   9978 non-null   float64
 9   High Blood Pressure   9974 non-null   object
 10  Low HDL Cholesterol   9975 non-null   object
 11  High LDL Cholesterol  9974 non-null   object
```

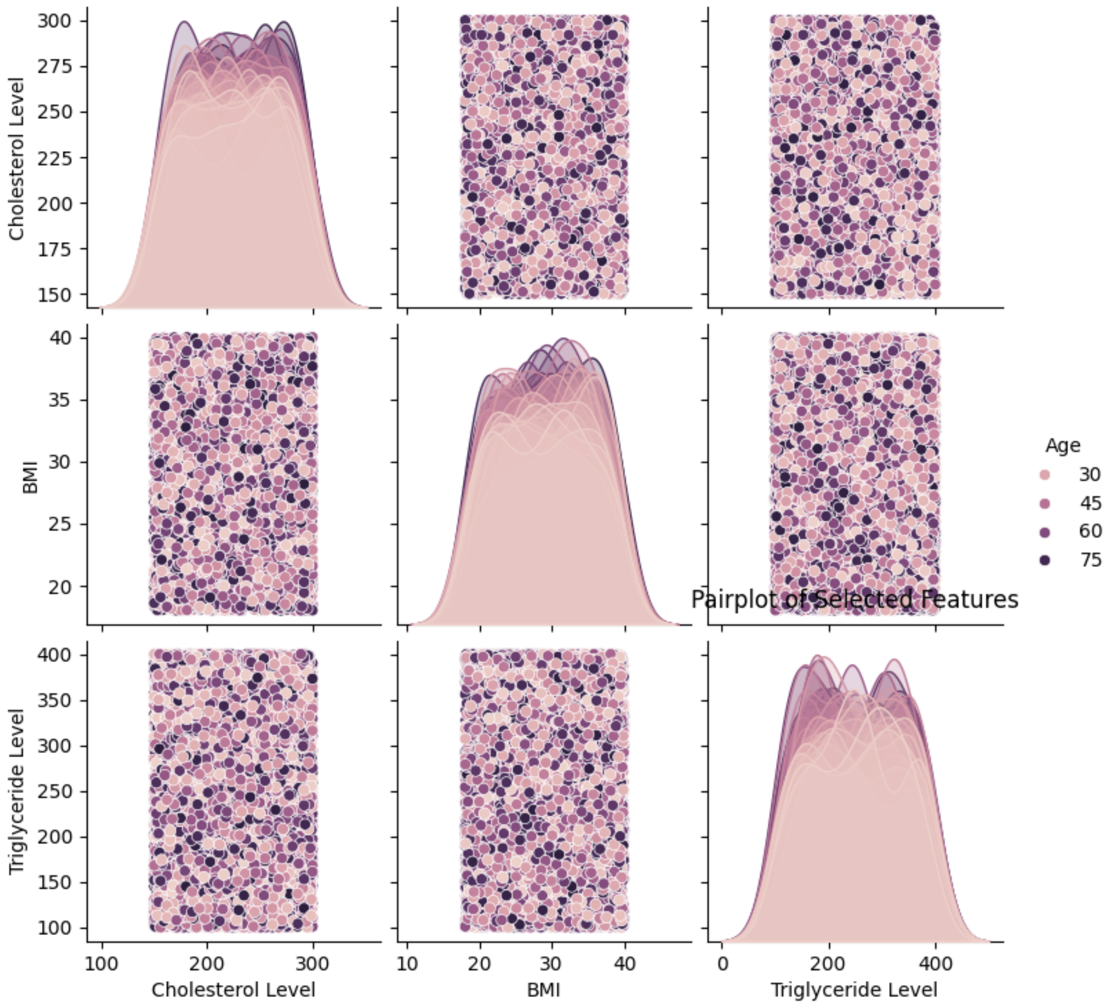
```
 12  Alcohol Consumption   7414 non-null   object
 13  Stress Level          9978 non-null   object
 14  Sleep Hours           9975 non-null   float64
 15  Sugar Consumption     9970 non-null   object
 16  Triglyceride Level    9974 non-null   float64
 17  Fasting Blood Sugar   9978 non-null   float64
 18  CRP Level             9974 non-null   float64
 19  Homocysteine Level    9980 non-null   float64
 20  Heart Disease Status  10000 non-null  object
dtypes: float64(9), object(12)
memory usage: 1.6+ MB
```

[13]:
```
df.corr(numeric_only=True)
```

[13]:
```
                          Age  Blood Pressure  Cholesterol Level       BMI  \
Age                  1.000000       -0.020781           0.011371  0.011229
Blood Pressure      -0.020781        1.000000          -0.012026  0.005405
Cholesterol Level    0.011371       -0.012026           1.000000  0.022002
BMI                  0.011229        0.005405           0.022002  1.000000
Sleep Hours          0.002481        0.001153           0.011195 -0.001029
Triglyceride Level  -0.008112        0.008108           0.001451  0.005354
Fasting Blood Sugar -0.006019       -0.011991           0.000060  0.006437
CRP Level            0.008779       -0.010137          -0.017564 -0.016525
Homocysteine Level  -0.007084       -0.003244          -0.006285  0.003583

                     Sleep Hours  Triglyceride Level  Fasting Blood Sugar  \
Age                     0.002481           -0.008112            -0.006019
Blood Pressure          0.001153            0.008108            -0.011991
Cholesterol Level       0.011195            0.001451             0.000060
BMI                    -0.001029            0.005354             0.006437
Sleep Hours             1.000000            0.002166             0.008586
Triglyceride Level      0.002166            1.000000             0.008086
Fasting Blood Sugar     0.008586            0.008086             1.000000
CRP Level               0.002067           -0.006413             0.010479
Homocysteine Level     -0.020280           -0.005727            -0.020404

                     CRP Level  Homocysteine Level
Age                   0.008779           -0.007084
Blood Pressure       -0.010137           -0.003244
Cholesterol Level    -0.017564           -0.006285
BMI                  -0.016525            0.003583
Sleep Hours           0.002067           -0.020280
Triglyceride Level   -0.006413           -0.005727
Fasting Blood Sugar   0.010479           -0.020404
CRP Level             1.000000           -0.010088
Homocysteine Level   -0.010088            1.000000
```

[14]:

```
sns.pairplot(df.loc[:, ['Age', 'Cholesterol Level', 'BMI', 'Triglyceride␣
    ↪Level']], hue='Age', diag_kind="kde")
plt.title("Pairplot of Selected Features")
plt.show()
```



Data Cleaning

[15]:

```
df.isna().sum()
```

[15]:

```
Age                     29
Gender                  19
Blood Pressure          19
Cholesterol Level       30
Exercise Habits         25
Smoking                 25
Family Heart Disease    21
```

```
Diabetes                  30
BMI                       22
High Blood Pressure       26
Low HDL Cholesterol       25
High LDL Cholesterol      26
Alcohol Consumption     2586
Stress Level              22
Sleep Hours               25
Sugar Consumption         30
Triglyceride Level        26
Fasting Blood Sugar       22
CRP Level                 26
Homocysteine Level        20
Heart Disease Status       0
dtype: int64
```

[17]:
```
# Menghapus kolom dengan lebih dari 30% nilai yang hilang
threshold = 0.3 * len(df)
df = df.dropna(axis=1, thresh=threshold)

# Menghapus baris yang memiliki nilai yang hilang
df = df.dropna()
```

[18]:
```
df.isna().sum()
```

[18]:
```
Age                     0
Gender                  0
Blood Pressure          0
Cholesterol Level       0
Exercise Habits         0
Smoking                 0
Family Heart Disease    0
Diabetes                0
BMI                     0
High Blood Pressure     0
Low HDL Cholesterol     0
High LDL Cholesterol    0
Alcohol Consumption     0
Stress Level            0
Sleep Hours             0
Sugar Consumption       0
Triglyceride Level      0
Fasting Blood Sugar     0
CRP Level               0
Homocysteine Level      0
Heart Disease Status    0
dtype: int64
```

[19]:
```
df.duplicated().sum()
```

[19]: 0

[20]:
```
df['Heart Disease Status'].value_counts()
```

[20]:
```
Heart Disease Status
No     5632
Yes    1435
Name: count, dtype: int64
```

[21]:
```
df['Family Heart Disease'].value_counts()
```

[21]:
```
Family Heart Disease
No     3540
Yes    3527
Name: count, dtype: int64
```

[22]:
```
df['Sugar Consumption'].value_counts()
```

[22]:
```
Sugar Consumption
Low       2403
High      2379
Medium    2285
Name: count, dtype: int64
```

[23]:
```
df['Gender'].value_counts()
```

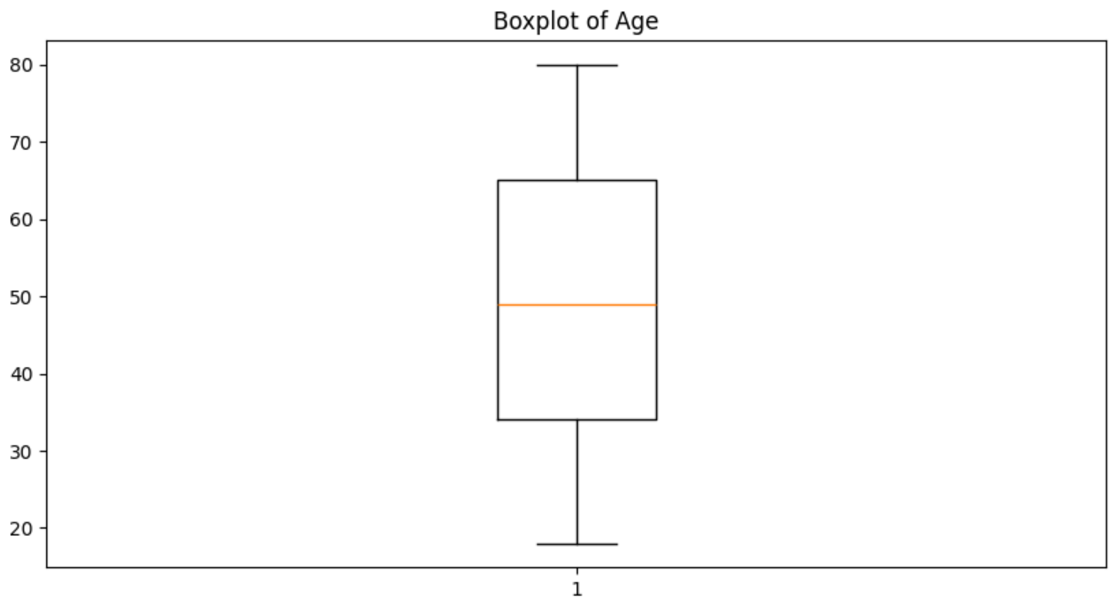
[23]:
```
Gender
Male      3564
Female    3503
Name: count, dtype: int64
```

[24]:
```
df['Cholesterol Level'].value_counts()
```

[24]:
```
Cholesterol Level
186.0    69
193.0    69
185.0    64
255.0    59
216.0    59
         ..
157.0    35
218.0    34
169.0    34
298.0    32
271.0    31
```

```
Name: count, Length: 151, dtype: int64
```

[25]:
```
plt.figure(figsize=(10,5))
plt.boxplot(df['Age'])
plt.title("Boxplot of Age")
plt.show()
```

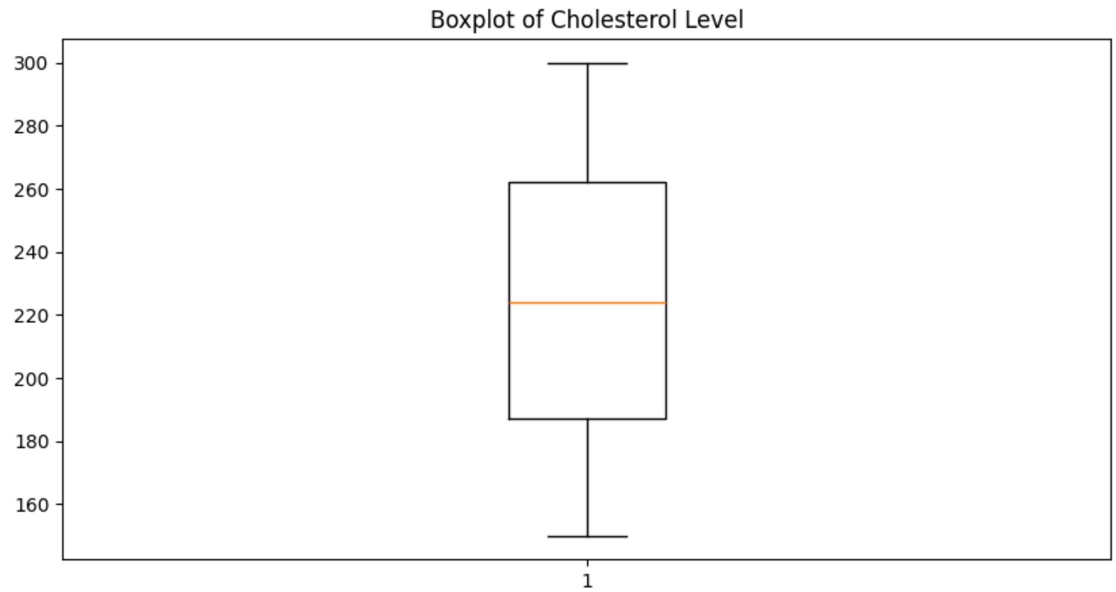


[26]:
```
#Remove outliers for Cholesterol Level using IQR
Q1 = df['Cholesterol Level'].quantile(0.25)
Q3 = df['Cholesterol Level'].quantile(0.75)
IQR = Q3 - Q1 #Interquartile range
```

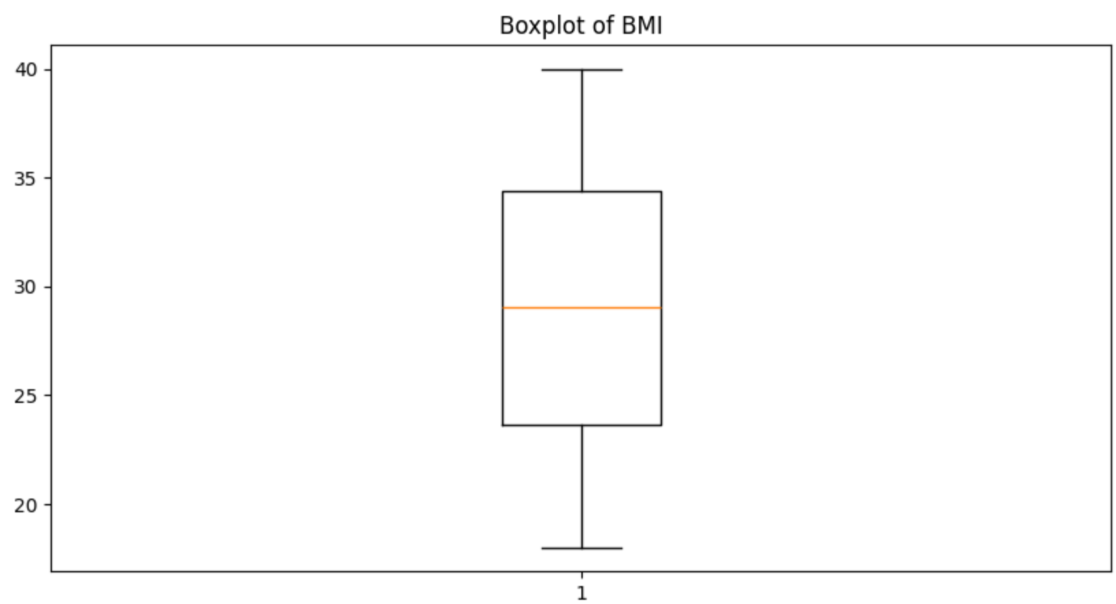
[29]:
```
#Calculate lower and upper bounds for outliers
min_range = Q1 - 1.5 * IQR
max_range = Q3 + 1.5 * IQR
```

[30]:
```
#Filter out rows with Cholesterol Level outside the bounds
df = df[(df['Cholesterol Level'] < max_range) & (df['Cholesterol Level'] >
  min_range)]
```

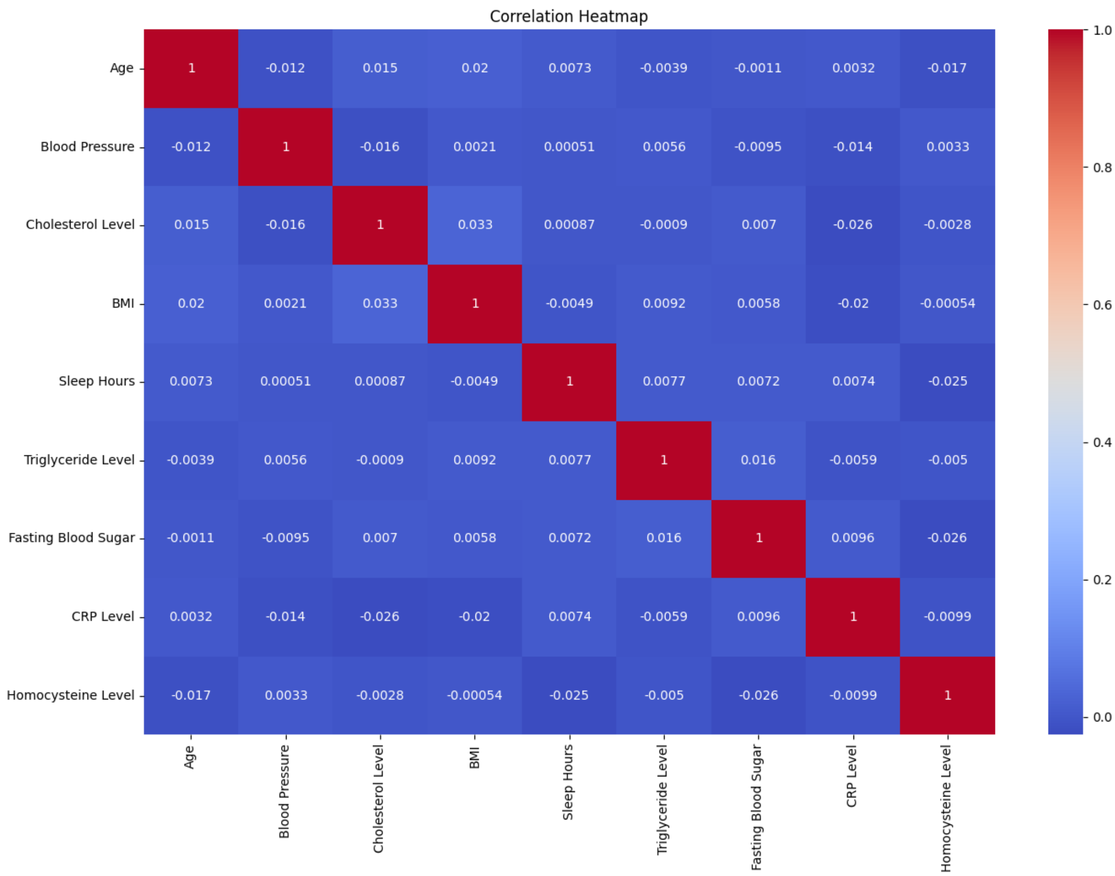
[31]:
```
#Boxplot for Cholesterol Level after removing otliers
plt.figure(figsize=(10,5))
plt.boxplot(df['Cholesterol Level'])
plt.title("Boxplot of Cholesterol Level")
plt.show()
```



[35]:
```
#Boxplot for BMI
plt.figure(figsize=(10,5))
plt.boxplot(df['BMI'])
plt.title("Boxplot of BMI")
plt.show()
```



```
[36]: #Heatmap to visualize correlations
plt.figure(figsize=(15,10))
var1= df.corr(numeric_only=True)
sns.heatmap(var1, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



Categorical Value Encoding

```
[38]: # Identify categorical columns
obj = []
for i in df.columns:
    if df[i].dtype == 'object':
        obj.append(i)

# Select columns for OneHotEncoding
Onehot_Enc = []
for i in obj:
    if len(df[i].unique()) > 2:  # Menggunakan len() untuk menghitung jumlah␣
 ↪nilai unik
```

```
        Onehot_Enc.append(i)
```

[39]:
```
#Apply OneHotEncoding to selected columns
onehot = OneHotEncoder(sparse_output=False, drop='first')
result = onehot.fit_transform(df[Onehot_Enc])
```

[40]:
```
#Create a DataFrame for encoded features
encoded_features = pd.DataFrame(result, columns=onehot.get_feature_names_out())
encoded_features
```

[40]:
```
      Exercise Habits_Low  Exercise Habits_Medium  Alcohol Consumption_Low  \
0                     0.0                     0.0                      0.0
1                     1.0                     0.0                      1.0
2                     0.0                     0.0                      1.0
3                     1.0                     0.0                      1.0
4                     1.0                     0.0                      1.0
…                     …                       …                        …
7062                  0.0                     1.0                      0.0
7063                  0.0                     1.0                      0.0
7064                  0.0                     1.0                      0.0
7065                  1.0                     0.0                      0.0
7066                  0.0                     1.0                      0.0

      Alcohol Consumption_Medium  Stress Level_Low  Stress Level_Medium  \
0                            1.0               0.0                  0.0
1                            0.0               1.0                  0.0
2                            0.0               0.0                  0.0
3                            0.0               0.0                  0.0
4                            0.0               0.0                  1.0
…                            …                 …                    …
7062                         1.0               1.0                  0.0
7063                         1.0               1.0                  0.0
7064                         1.0               0.0                  0.0
7065                         1.0               0.0                  0.0
7066                         0.0               0.0                  1.0

      Sugar Consumption_Low  Sugar Consumption_Medium
0                       0.0                       1.0
1                       1.0                       0.0
2                       0.0                       0.0
3                       0.0                       0.0
4                       1.0                       0.0
…                       …                         …
7062                    0.0                       0.0
7063                    0.0                       1.0
7064                    0.0                       1.0
7065                    0.0                       1.0
```

```
7066                    0.0                       0.0

[7067 rows x 8 columns]
```

[41]:
```python
#Drop original columns replaced by encoded features
df.drop(columns=Onehot_Enc, axis=1)
```

[41]:
```
       Age  Gender  Blood Pressure  Cholesterol Level Smoking  \
1     69.0  Female           146.0              286.0      No
2     46.0    Male           126.0              216.0      No
3     32.0  Female           122.0              293.0     Yes
4     60.0    Male           166.0              242.0     Yes
5     25.0    Male           152.0              257.0     Yes
…      …     …              …                 …       …
9992  68.0  Female           169.0              291.0     Yes
9994  73.0  Female           144.0              191.0     Yes
9995  25.0  Female           136.0              243.0     Yes
9998  23.0    Male           142.0              299.0     Yes
9999  38.0  Female           128.0              193.0     Yes

     Family Heart Disease Diabetes        BMI High Blood Pressure  \
1                     Yes      Yes  25.221799                  No
2                      No       No  29.855447                  No
3                     Yes       No  24.130477                 Yes
4                     Yes      Yes  20.486289                 Yes
5                      No       No  28.144681                  No
…                     …       …        …                 …
9992                   No       No  22.839718                  No
9994                  Yes      Yes  39.459620                  No
9995                   No       No  18.788791                 Yes
9998                   No      Yes  34.964026                 Yes
9999                  Yes      Yes  25.111295                  No

     Low HDL Cholesterol High LDL Cholesterol  Sleep Hours  \
1                    Yes                   No     8.744034
2                    Yes                  Yes     4.440440
3                     No                  Yes     5.249405
4                     No                   No     7.030971
5                     No                   No     5.504876
…                   …                   …          …
9992                 Yes                   No     6.057509
9994                  No                   No     7.549114
9995                  No                  Yes     6.834954
9998                  No                  Yes     8.526329
9999                 Yes                  Yes     5.659394

      Triglyceride Level  Fasting Blood Sugar  CRP Level  Homocysteine Level  \
```

```
1               133.0               157.0   9.355389           19.298875
2               393.0                92.0  12.709873           11.230926
3               293.0                94.0  12.509046            5.961958
4               263.0               154.0  10.381259            8.153887
5               126.0                91.0   4.297575           10.815983
…               …                  …        …                 …
9992            299.0               142.0   3.321020           11.910244
9994            200.0                88.0   1.154904            8.021732
9995            343.0               133.0   3.588814           19.132004
9998            113.0               153.0   7.215634           11.873486
9999            121.0               149.0  14.387810            6.208531

     Heart Disease Status
1                      No
2                      No
3                      No
4                      No
5                      No
…                     …
9992                  Yes
9994                  Yes
9995                  Yes
9998                  Yes
9999                  Yes

[7067 rows x 17 columns]
```

[42]:
```python
#Reset index for consistency
df.reset_index(drop=True, inplace=True)
```

[43]:
```python
#Merge the encoded features back into the dataset
df = df.join(encoded_features)
```

[68]:
```python
x = df.drop('Heart Disease Status', axis=1)
y = df['Heart Disease Status']

# Mengonversi kolom kategorikal menjadi numerik menggunakan One-Hot Encoding
x = pd.get_dummies(x, drop_first=True)  # drop_first=True untuk menghindari␣
 ↪dummy variable trap
```

[69]:
```python
# Handle class imbalance using SMOTE
smote = SMOTE(random_state=42)
x_resampled, y_resampled = smote.fit_resample(x, y)
```

[70]:
```python
# Menampilkan hasil
print(x_resampled.shape, y_resampled.shape)
```

```
(11264, 32) (11264,)
```

[71]:
```python
#Check the class distribution after SMOTE
y_resampled.value_counts()
```

[71]:
```
Heart Disease Status
No     5632
Yes    5632
Name: count, dtype: int64
```

[72]:
```python
#Normalize feature values using MinMAxScaler
minmax = MinMaxScaler()
x_resampled = minmax.fit_transform(x_resampled)
```

[73]:
```python
#Split the dataset into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x_resampled, y_resampled,␣
 ↪test_size=0.23, random_state=10)
```

Model Evaluation

[74]:
```python
#Train and evaluate a KNN Classifier
knn = KNeighborsClassifier(n_neighbors=11, weights='distance',␣
 ↪metric='manhattan')
knn.fit(x_train, y_train)
y_pred = knn.predict(x_test)
```

[75]:
```python
#Evaluate the model
print(f"Accuracy Score: {accuracy_score(y_test, y_pred)}")
print(f"Classification Report:\n{classification_report(y_test, y_pred)}")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred)}")
```

```
Accuracy Score: 0.8340409108452335
Classification Report:
              precision    recall  f1-score   support

          No       0.79      0.92      0.85      1323
         Yes       0.90      0.75      0.81      1268

    accuracy                           0.83      2591
   macro avg       0.84      0.83      0.83      2591
weighted avg       0.84      0.83      0.83      2591

Confusion Matrix:
[[1214  109]
 [ 321  947]]
```

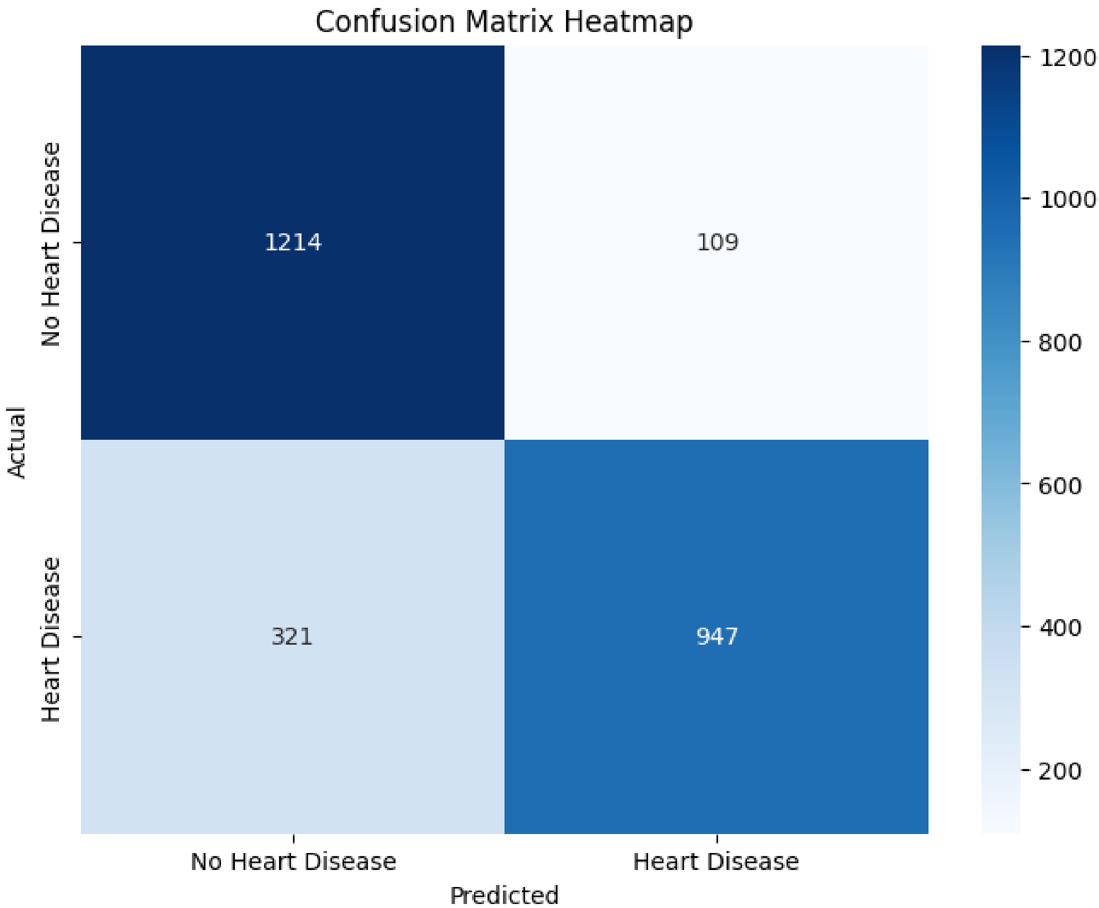
[77]:
```python
#Loop through addtional model (if needed)
```

```
models =[KNeighborsClassifier(n_neighbors=11, weights='distance',␣
 ↪metric='manhattan')]
for model in models :
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    print(f"Accuracy Score of {model}: {accuracy_score(y_test, y_pred)}")
    print("-----------------------------")
    print(f"Classification Report of {model}:\n{classification_report(y_test,␣
 ↪y_pred)}")
    print("-----------------------------")
    print(f"Confusion Matrix of {model}:\n{confusion_matrix(y_test, y_pred)}")
```

```
Accuracy Score of KNeighborsClassifier(metric='manhattan', n_neighbors=11,
weights='distance'): 0.8340409108452335
-----------------------------
Classification Report of KNeighborsClassifier(metric='manhattan',
n_neighbors=11, weights='distance'):
              precision    recall  f1-score   support

          No       0.79      0.92      0.85      1323
         Yes       0.90      0.75      0.81      1268

    accuracy                           0.83      2591
   macro avg       0.84      0.83      0.83      2591
weighted avg       0.84      0.83      0.83      2591

-----------------------------
Confusion Matrix of KNeighborsClassifier(metric='manhattan', n_neighbors=11,
weights='distance'):
[[1214  109]
 [ 321  947]]
```

[78]:

```
#Plot heatmap of the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No␣
 ↪Heart Disease', 'Heart Disease'], yticklabels=['No Heart Disease', 'Heart␣
 ↪Disease'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



Heart Attack Prediction Insights

1. Dataset Overview

The dataset consists of 10,000 records and 21 features, covering various factors that influence heart disease, including: * Demographics: Age, Gender * Medical Conditions: Blood Pressure, Cholesterol Levels, Diabetes, BMI * Lifestyle Factors: Smoking, Exercise Habits, Alcohol Consumption, Stress Level, Sleep Hours * Clinical Metrics: Triglyceride Level, Fasting Blood Sugar, C-Reactive Protein (CRP) Level, Homocysteine Level * Target Variable: Heart Disease Status (Yes/No)

After cleaning the dataset, the final data used for modeling contained 7,067 records with no missing values.

2. Exploratory Data Analysis (EDA)

EDA was conducted to understand correlations between variables and their impact on heart disease. Key findings include: * Age & Cholesterol Levels: Older individuals tend to have higher cholesterol levels, increasing heart disease risk. * Smoking & High Blood Pressure: A strong correlation was observed between smoking and high blood pressure. * Stress & Sleep: Higher stress levels were associated with lower sleep hours, which can indirectly contribute to heart disease. * Correlation Heatmap: Showed that Cholesterol Level, Blood Pressure, and Diabetes had a notable relationship with heart disease.

3. Data Preprocessing

To ensure data quality, the following preprocessing steps were performed:

Handling Missing Data: * Columns with more than 30% missing values (e.g., Alcohol Consumption) were dropped. * Remaining missing values were removed to maintain data integrity.

Encoding Categorical Variables: * One-Hot Encoding was applied to categorical variables like Exercise Habits, Sugar Consumption, and Stress Level to convert them into numerical form.

Handling Class Imbalance: * SMOTE (Synthetic Minority Over-sampling Technique) was applied to balance the dataset since the original data had significantly more "No Heart Disease" cases. * After SMOTE, the dataset had an equal distribution of 5,632 "No" cases and 5,632 "Yes" cases.

Feature Scaling: * MinMaxScaler was used to normalize numerical features for better model performance.

4. Model Building & Evaluation

The K-Nearest Neighbors (KNN) classifier was chosen for prediction.

Best Model Parameters: * K = 11 neighbors * Distance Metric = Manhattan Distance * Weighting = Distance-based

Performance Metrics: * Accuracy: 83.4% * Precision & Recall: The model had higher precision in predicting non-heart disease cases but lower recall for heart disease cases. * Confusion Matrix: Showed some false negatives, meaning a few heart disease cases were misclassified.

5. Visualization Insights

- Pairplot Analysis: Highlighted how cholesterol and BMI patterns differed between heart disease and non-heart disease cases.
- Boxplots for Outlier Detection: Cholesterol & BMI had extreme values, and an interquartile range (IQR) approach was used to remove outliers.
- Confusion Matrix Heatmap: Showed that the model was better at predicting no heart disease cases than identifying patients with heart disease.

6. Key Changes & Improvements

- Before applying SMOTE, the model was biased towards predicting "No Heart Disease", leading to high false negatives.
- After SMOTE, the recall improved, making the model more reliable for early heart disease detection.
- Feature Selection & Normalization improved model consistency and generalization.

7. Future Scope & Enhancements

To improve accuracy and robustness, future enhancements could include: * Trying Advanced Models: Testing Random Forest, XGBoost, and Deep Learning approaches for better performance. * Incorporating More Features: Adding physical activity levels, dietary habits, and genetic factors could provide better predictions. * Feature Engineering: Creating new interaction variables to capture hidden patterns. * Deploying the Model: Integrating the model into a real-time monitoring system for predictive healthcare applications.

Conclusion

This heart attack prediction model provides **a data-driven approach to identifying high-risk individuals** based on medical and lifestyle factors. While the current **model achieves an 83.4% accuracy**, further improvements can be made by experimenting with different algorithms and incorporating additional patient history data.

By leveraging machine learning for **preventive healthcare**, we can move towards** early detection, better treatment planning, and improved patient outcomes**.