Heart Attack SHAP Practice (v2.1)

July 12, 2022

[1]:

```
# This Heart Attack data Logistic Regression model is based on the 'heart.csv'
#                 file (heart attack dataset from Kaggle)
# NOTE: Please do not take values as is, this is only a rough implementation of␣
↪a LR ML model
#       Goal of this project is to show various ways SHAP can explain (and show)␣
↪contribution
#                 of each feature in the dataset
#       SHAP implementation is usually best for tree-based ML models such as
#                 RandomForest, DecisionTree, etc




# More info on this dataset:

# Age : Age of the patient
# Sex : Sex of the patient
# cp : Chest Pain type
#             Value 0: typical angina
#             Value 1: atypical angina
#             Value 2: non-anginal pain
#             Value 3: asymptomatic


# trtbps : resting blood pressure (in mm Hg)
# chol: cholesterol in mg/dl fetched via BMI sensor
# fbs: (fasting blood sugar > 120 mg/dl)
#             1 = true
#             0 = false


# rest_ecg: resting electrocardiographic results
#             Value 0: normal
#             Value 1: having ST-T wave abnormality (T wave inversions and/or ST␣
↪elevation or depression of > 0.05 mV)
#             Value 2: showing probable or definite left ventricular hypertrophy␣
↪by Estes
```

```
# thalach: maximum heart rate achieved
# exang: exercise induced angina
#             1 = yes
#             0 = no


# old peak: ST depression induced by exercise relative to rest
# slp: the slope of the peak exercise ST segment
#             0 = unsloping
#             1 = flat
#             2 = downsloping


# caa: number of major vessels (0-3)
# thall : thalassemia
#             0 = null
#             1 = fixed defect
#             2 = normal
#             3 = reversable defect


# output: diagnosis of heart disease (angiographic disease status)
#             0: < 50% diameter narrowing. less chance of heart disease
#             1: > 50% diameter narrowing. more chance of heart disease
```

[2]:

```
import os
import numpy as np
import pandas as pd
import matplotlib as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import shap
import xgboost
import catboost as cb
from termcolor import colored as cl #text customization
from scipy.special import softmax
!export PATH=/Library/TeX/texbin:$PATH
shap.initjs() # load JS visualization code to notebook. SHAP plots won't be␣
 ↪displayed without this
```

<IPython.core.display.HTML object>

[3]:

```
# Phase 1: import data
```

```python
data = pd.read_csv('heart.csv')
data.head()

#print('\n', data.describe()) # this will show stats on each feature
```

[3]:
```
   age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng  oldpeak  slp  \
0   63    1   3     145   233    1        0       150     0      2.3    0
1   37    1   2     130   250    0        1       187     0      3.5    0
2   41    0   1     130   204    0        0       172     0      1.4    2
3   56    1   1     120   236    0        1       178     0      0.8    2
4   57    0   0     120   354    0        1       163     1      0.6    2

   caa  thall  output
0    0      1       1
1    0      2       1
2    0      2       1
3    0      2       1
4    0      2       1
```

[4]:
```python
# Phase 2: Splitting dataset into X and y based on row and column using iloc[]
#          and reshaping X-variable before training and testing

X = data.iloc[:, :-1]
y = data.iloc[:, -1]

print('\nChecking X-variable before scaling\n', X)
print('\nChecking values in y\n', y)


# data partitioning
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)


scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
print('\nChecking X-variable values after scaling\n', X_train)




# Checking training and testing samples for train_test_split
print('\nChecking data partitioning\nX_train samples: {}\n\nX_test samples:␣
↪{}\n\ny_train samples: {}\n\ny_test samples: {}'.format(X_train, X_test,␣
↪y_train, y_test))
```

```
Checking X-variable before scaling
     age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng  oldpeak  slp  \
```

```
0     63   1  3   145  233  1      0      150   0     2.3   0
1     37   1  2   130  250  0      1      187   0     3.5   0
2     41   0  1   130  204  0      0      172   0     1.4   2
3     56   1  1   120  236  0      1      178   0     0.8   2
4     57   0  0   120  354  0      1      163   1     0.6   2
..   ...  ... ..  ...  ...  ...    ...    ...  ...    ...  ...
298   57   0  0   140  241  0      1      123   1     0.2   1
299   45   1  3   110  264  0      1      132   0     1.2   1
300   68   1  0   144  193  1      1      141   0     3.4   1
301   57   1  0   130  131  0      1      115   1     1.2   1
302   57   0  1   130  236  0      0      174   0     0.0   1

     caa  thall
0      0      1
1      0      2
2      0      2
3      0      2
4      0      2
..   ...    ...
298    0      3
299    0      3
300    2      3
301    1      3
302    1      2

[303 rows x 13 columns]

Checking values in y
 0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: output, Length: 303, dtype: int64

Checking X-variable values after scaling
 [[ 1.2074225   0.68849544 -0.95607147 ...  0.99874214 -0.70333816
   1.10304227]
 [ 0.87070886 -1.45244244 -0.95607147 ... -0.64411631 -0.70333816
  -0.55517359]
 [ 0.30951945  0.68849544  0.9730683  ...  0.99874214 -0.70333816
  -0.55517359]
```

```
 ...
 [ 0.87070886  0.68849544  0.00849841 ...  0.99874214 -0.70333816
  -0.55517359]
 [ 0.30951945 -1.45244244  0.00849841 ... -0.64411631  0.27018478
  -0.55517359]
 [ 0.98294674  0.68849544 -0.95607147 ...  0.99874214  2.21723067
   1.10304227]]

Checking data partitioning
X_train samples: [[ 1.2074225   0.68849544 -0.95607147 ...  0.99874214
-0.70333816
   1.10304227]
 [ 0.87070886 -1.45244244 -0.95607147 ... -0.64411631 -0.70333816
  -0.55517359]
 [ 0.30951945  0.68849544  0.9730683  ...  0.99874214 -0.70333816
  -0.55517359]
 ...
 [ 0.87070886  0.68849544  0.00849841 ...  0.99874214 -0.70333816
  -0.55517359]
 [ 0.30951945 -1.45244244  0.00849841 ... -0.64411631  0.27018478
  -0.55517359]
 [ 0.98294674  0.68849544 -0.95607147 ...  0.99874214  2.21723067
   1.10304227]]

X_test samples:      age  sex  cp  trtbps  chol  fbs  restecg  thalachh  exng
oldpeak  slp  \
209   59    1   0     140   177    0        1       162     1      0.0    2
5     57    1   0     140   192    0        1       148     0      0.4    1
299   45    1   3     110   264    0        1       132     0      1.2    1
274   47    1   0     110   275    0        0       118     1      1.0    1
59    57    0   0     128   303    0        0       159     0      0.0    2
..   ...  ...  ..     ...   ...  ...      ...       ...   ...      ...  ...
60    71    0   2     110   265    1        0       130     0      0.0    2
221   55    1   0     140   217    0        1       111     1      5.6    0
199   65    1   0     110   248    0        0       158     0      0.6    2
197   67    1   0     125   254    1        1       163     0      0.2    1
257   50    1   0     144   200    0        0       126     1      0.9    1

     caa  thall
209    1      3
5      0      1
299    0      3
274    1      2
59     1      2
..   ...    ...
60     1      2
221    0      3
199    2      1
```

```
197    2      3
257    0      3

[76 rows x 13 columns]

y_train samples: 31     1
258    0
9      1
28     1
90     1
      ..
113    1
284    0
137    1
302    0
217    0
Name: output, Length: 227, dtype: int64

y_test samples: 209    0
5      1
299    0
274    0
59     1
      ..
60     1
221    0
199    0
197    0
257    0
Name: output, Length: 76, dtype: int64
```

[5]:

```
# Phase 3: Creating the model
# Understanding LR parameters:
#                solver = a string ('liblinear' by deafult) that decides what␣
↪solver to use for fitting the model
#                multi-class = a string ('ovr' by default) decides the approach␣
↪to use for handling multiple classes\
#                              'ovr' says to make the binary fit for each class
#                               'multinomial' says to apply the multinomial loss␣
↪fit
#                C = a positive floating-point number (1.0 by default) that␣
↪defines the relative strength of regularization
#                random_state = an integer, an instance of numpy.RandomState, or␣
↪None (default) that defines what pseudo number

model = LogisticRegression(solver='liblinear', C=0.5, multi_class='ovr',␣
↪random_state=0)
```

```
model.fit(X_train, y_train)

print('\nChecking LR output string\n', cl(model, attrs = ['bold']))
print('\nChecking LR coefficients: \n', model.coef_)
print('\nChecking LR intercept: \n', model.intercept_)
```

```
Checking LR output string
 LogisticRegression(C=0.5, multi_class='ovr', random_state=0,

solver='liblinear')

Checking LR coefficients:
 [[ 0.04938564 -0.48975268  1.02199574 -0.35408865  0.05784901  0.05261735
   0.41202293  0.24570615 -0.5247825  -0.60006623  0.35173065 -0.67646986
  -0.43941142]]

Checking LR intercept:
 [0.25759399]
```

[6]:
```
# Phase 4:Evaluating the model: returns the matrix of probabilities

X_test = scaler.transform(X_test)
y_pred = model.predict(X_test)
confusion_matrix(y_test, y_pred)
```

[6]:
```
array([[29, 10],
       [ 4, 33]])
```

[7]:
```
train_score = model.score(X_train, y_train)
test_score = model.score(X_test, y_test)
print('\nTrain score is: \n', train_score)
print('\nTest score is: \n', test_score)
```

```
Train score is:
 0.8502202643171806

Test score is:
 0.8157894736842105
```

[8]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.74      0.81        39
           1       0.77      0.89      0.82        37
```

```
    accuracy                           0.82        76
   macro avg       0.82      0.82      0.82        76
weighted avg       0.82      0.82      0.82        76
```

[9]:
```
# Phase 5: Creating SHAP explainer object
#           Creating feature_names array to store features to be able to use in␣
 ↪shap plots/graphs


feature_names = []
for feature in X.columns.tolist():
    feature_names.append(feature)
print('\nChecking feature names in columns from X-variable: \n', feature_names)




# Because we are using a LogisticRegression model which is a type of linear␣
 ↪model, we want to use
#           the .LinearExplainer() SHAP method
# Use train data for masker -- > based on usual train/test paradigm, where you␣
 ↪train your model
#           (and explainer) on train data, and try to predict (and explain) your␣
 ↪test data.
#           (troubleshoot: https://stackoverflow.com/questions/66560839/
 ↪what-do-maskers-really-do-
#                              in-shap-package-and-fit-them-to-train-or-test)
#masker = shap.maskers.Independent(data = X_train)
#explainer = shap.LinearExplainer(model, masker = masker)
# Uncomment masker and explainer w/masker arg, Comment .Explainer to see actual␣
 ↪representation (not
#            necessarily accurate).  Doing this will cause labels on SHAP plots/
 ↪graphs to display
#            'Feature #' instead of actual feature name


explainer = shap.Explainer(model.predict, X_test, feature_names=feature_names)
shap_values = explainer(X_train)
```

```
Checking feature names in columns from X-variable:
 ['age', 'sex', 'cp', 'trtbps', 'chol', 'fbs', 'restecg', 'thalachh', 'exng',
'oldpeak', 'slp', 'caa', 'thall']
```

[10]:
```
# OPTIONAL: Take the mean average value of each feature to get feature␣
 ↪importances dtermined by SHAP
```

```
# NOTE:     This is to only showcase how SHAP feature importance works (not my␣
↪own code, just put it
#                       in here to provide comprehensive baseline of how SHAP␣
↪and feature importance
#                       work)
# CREDIT:   Vinícius Trevisan (only this cell of the code)
#           https://towardsdatascience.com/
↪using-shap-values-to-explain-how-your-machine-learning-model-works-732b3f40e137

#def print_feature_importances_shap_values(shap_values, feature_names):
#     '''
#     Prints the feature importances based on SHAP values in an ordered way
#     shap_values -> The SHAP values calculated from a shap.Explainer object
#     features -> The name of the features, on the order presented to the␣
↪explainer
#     '''
# # Calculates the feature importance (mean absolute shap value) for each feature
#     importances = []
#     for i in range(shap_values.values.shape[1]):
#         importances.append(np.mean(np.abs(shap_values.values[:, i])))
# # Calculates the normalized version
#     importances_norm = softmax(importances)
# # Organize the importances and columns in a dictionary
#     feature_importances = {fea: imp for imp, fea in zip(importances,␣
↪feature_names)}
#     feature_importances_norm = {fea: imp for imp, fea in zip(importances_norm,␣
↪feature_names)}
# # Sorts the dictionary
#     feature_importances = {key:value for key, value in␣
↪sorted(feature_importances.items(), key=lambda item: item[1], reverse = True)}
#     feature_importances_norm= {key:value for key,value in␣
↪sorted(feature_importances_norm.items(), key=lambda item: item[1], reverse =␣
↪True)}
# # Prints the feature importances
#     for key, value in feature_importances.items():
#         print(f"{key} -> {value:.4f} (softmax = {feature_importances_norm[key]:
↪.4f})")

# print_feature_importances_shap_values(shap_values, feature_names)
```

[11]:
```
#  Phase 5a: Finding 'best' way to represent dataset using SHAP visualizations
#  NOTE: Please do not take values as is, this is only a rough implementation of␣
↪a LR model
#        Goal of this project is to show various ways SHAP can explain (and␣
↪show) contribution
#                of each feature in the dataset
```

```
# for-loop goes through shap_values which stores .base_values, .values, .data␣
↪while also looping
#             through feature_names to assign respective shap_value to its␣
↪corresponding feature name
# Break the inner loop to execute string based on length of the feature_names␣
↪array or else inner-loop
#             will repeat string format all # of times of length in feature_names
# The shap_values variable will have three attributes: .values, .base_values and␣
↪.data.
# The .data attribute is simply a copy of the input data, .base_values is the␣
↪expected value of the
#             target, or the average target value of all the train data, and .
↪values are the SHAP
#             values for each example.
# If we are only interested in the SHAP values, we can use the explainer.
↪shap_values() method

# If we are only interested in the SHAP values, we can use the explainer.
↪shap_values() method:
print('\nArray of SHAP values with added feature_names: ')
for name in feature_names:
    print('\n')
    for value in shap_values:
        print('"{}" data and values \n{}'.format(name, value))
        break



# By default, a SHAP beeswarm plot will take the mean absolute value of each␣
↪feature
#              over all the instances (rows) of the dataset
# Each point on the chart is one SHAP value for a prediction and feature
# Red color means higher value of a feature. Blue means lower value of a feature.
# We can get the general sense of features' directionality impact based on the␣
↪distribution of
#             the red and blue dots
print('\nPrinting Beeswarm SHAP Plot: \n')
shap.plots.beeswarm(shap_values)


# In this chart, the x-axis stands for the SHAP value and the y-axis has all the␣
↪features
```

```python
print('\nPrinting Summary SHAP Bar Plot: \n')
shap.summary_plot(shap_values, feature_names, plot_type='bar')



# Interesting SHAP scatter plot summary of all SHAP values for each feature
print('\nPrinting Scatter SHAP Plot for All Features: \n')
shap.plots.scatter(shap_values[:,:])


# for-loop for SHAP scatter plots to show correlation between different features
print('\nPrinting Scatter SHAP Plot Between Features: \n')
for feature in feature_names:
    shap.plots.scatter(shap_values[:, feature], color=shap_values)


# For analysis of local, instance-wise effects, we can use the following plots␣
 ↪on single
#               observations using "shap_values[0]".
print('\nPrinting Bar SHAP Plot for Local, Instance-Wise Effects: \n')
shap.plots.bar(shap_values[0])


# The waterfall plot has the same information, represented in a different manner.
 ↪
# Here we can see how the sum of all the SHAP values equals the difference␣
 ↪between
#               the prediction f(x) and the expected value E[f(x)].
print('\nPrinting Waterfall SHAP Plot for Local, Instance-Wise Effects: \n')
shap.plots.waterfall(shap_values[0])


# In this plot the positive SHAP values are displayed on the left side and the␣
 ↪negative on the
#               right side, as if competing against each other. The highlighted␣
 ↪value is the
#               prediction for that observation.
# Note that this is for a single instance
print('\nPrinting Force SHAP Plot for Local, Instance-Wise Effects: \n')
shap.plots.force(shap_values[0])
```

```
Array of SHAP values with added feature_names:


"age" data and values
.values =
```

```
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"sex" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"cp" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"trtbps" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])
```

```
.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"chol" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"fbs" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"restecg" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105
```

```
.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"thalachh" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"exng" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])


"oldpeak" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
```

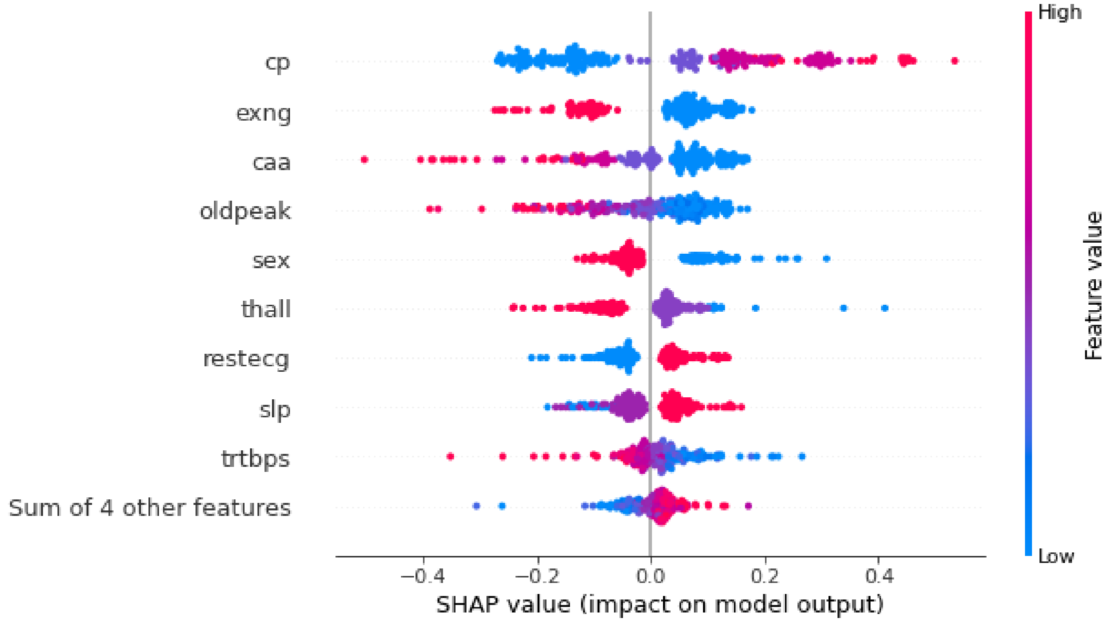
```
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])
```

```
"slp" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])
```

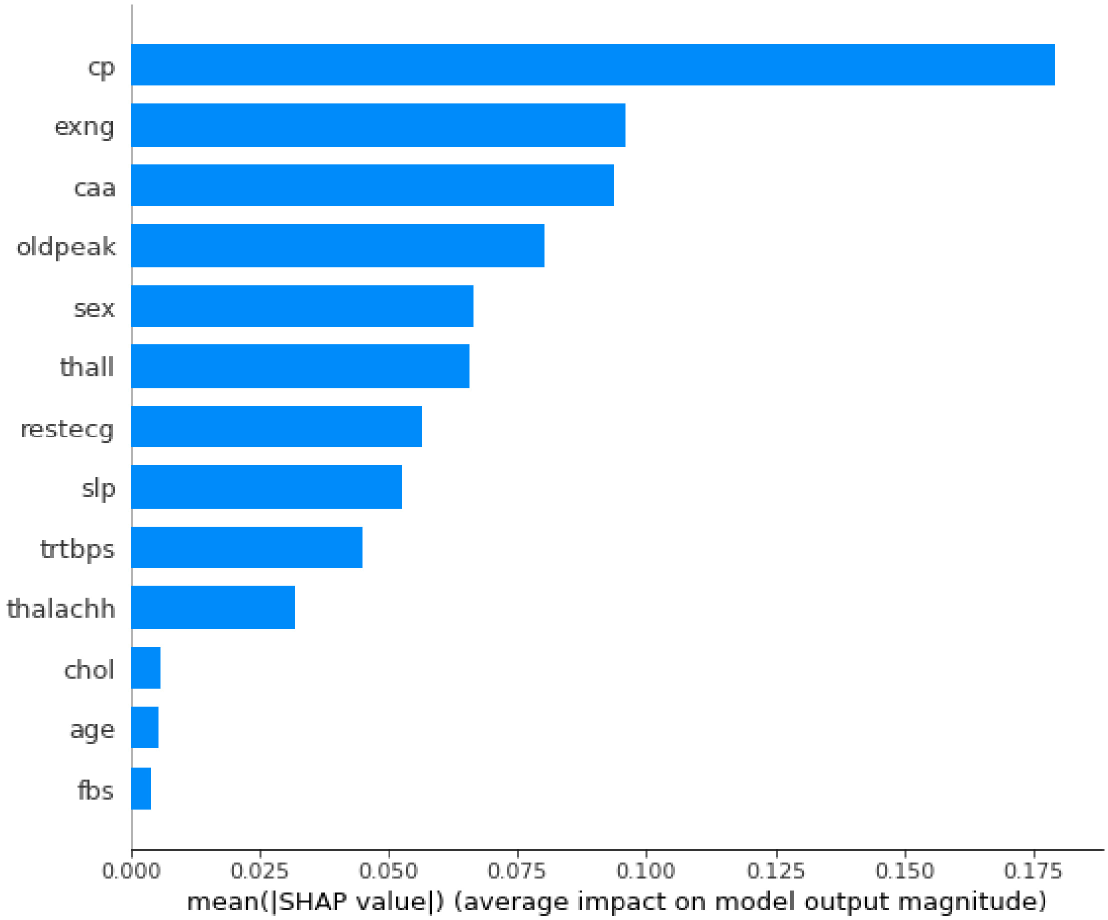
```
"caa" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])
```

```
"thall" data and values
.values =
array([ 0.01023392, -0.06688596, -0.13450292,  0.08479532, -0.00657895,
       -0.00402047,  0.13596491, -0.01754386,  0.12426901,  0.08077485,
        0.15899123,  0.16959064, -0.10087719])

.base_values =
0.5657894736842105

.data =
array([ 1.2074225 ,  0.68849544, -0.95607147, -0.64519349, -1.31346187,
       -0.43414476,  0.93849623, -0.4464528 , -0.6815542 , -0.57895484,
        0.99874214, -0.70333816,  1.10304227])
```

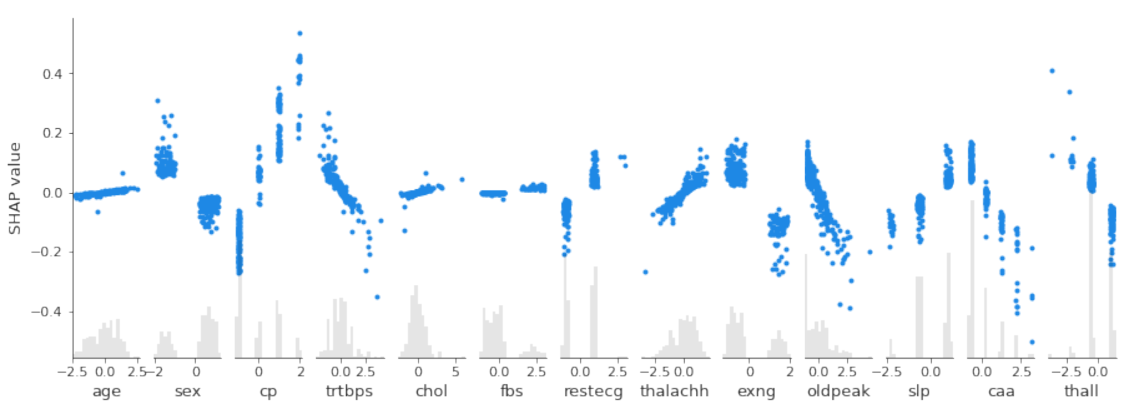
Printing Beeswarm SHAP Plot:



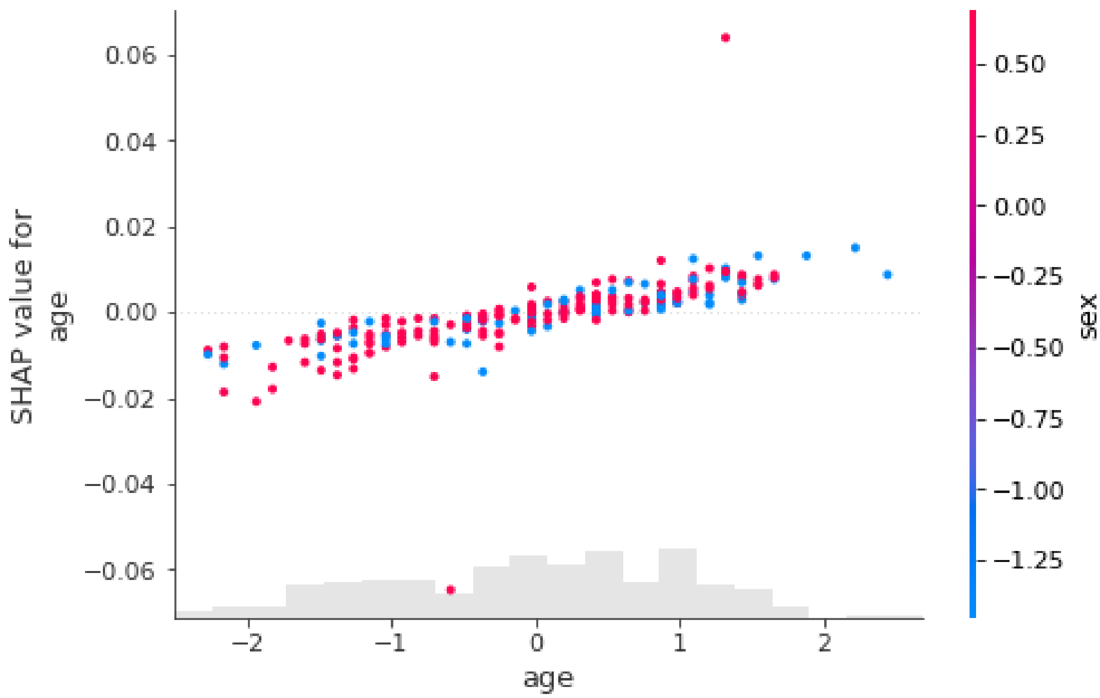
Printing Summary SHAP Bar Plot:

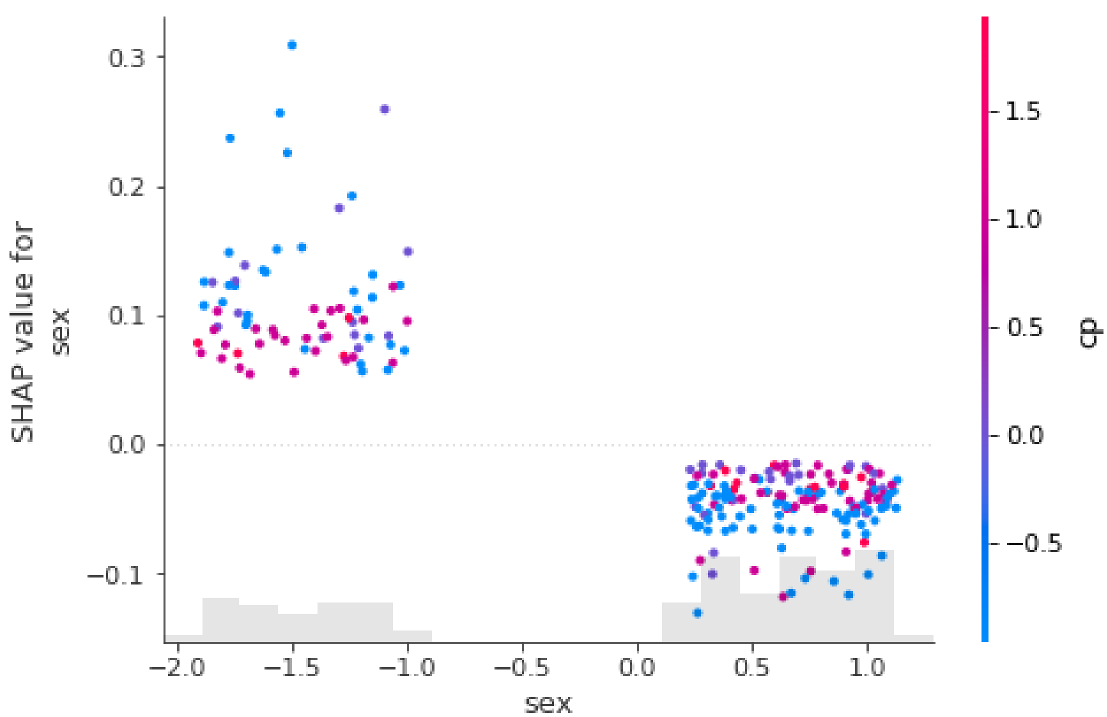


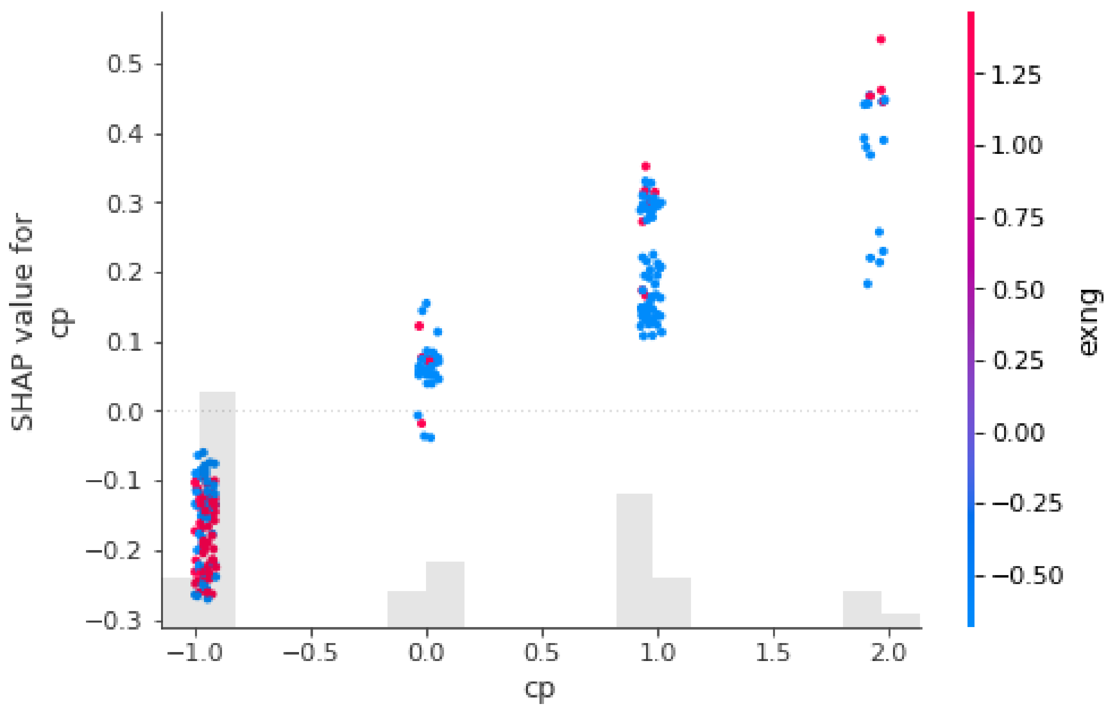

```
Printing Scatter SHAP Plot for All Features:
```

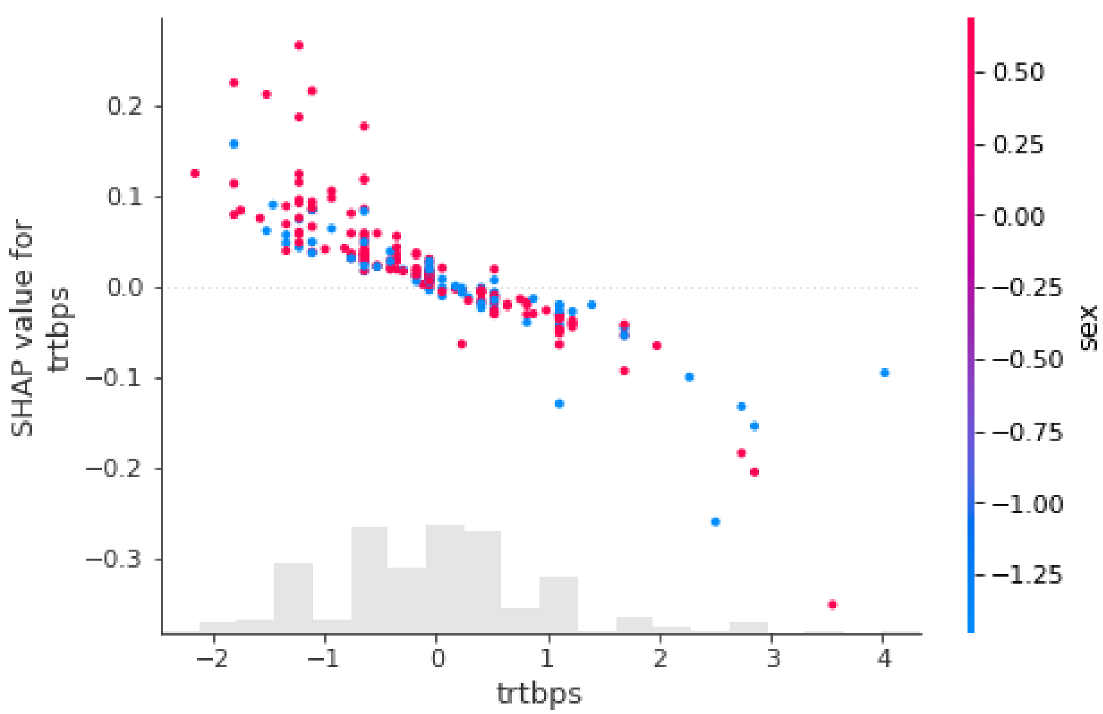


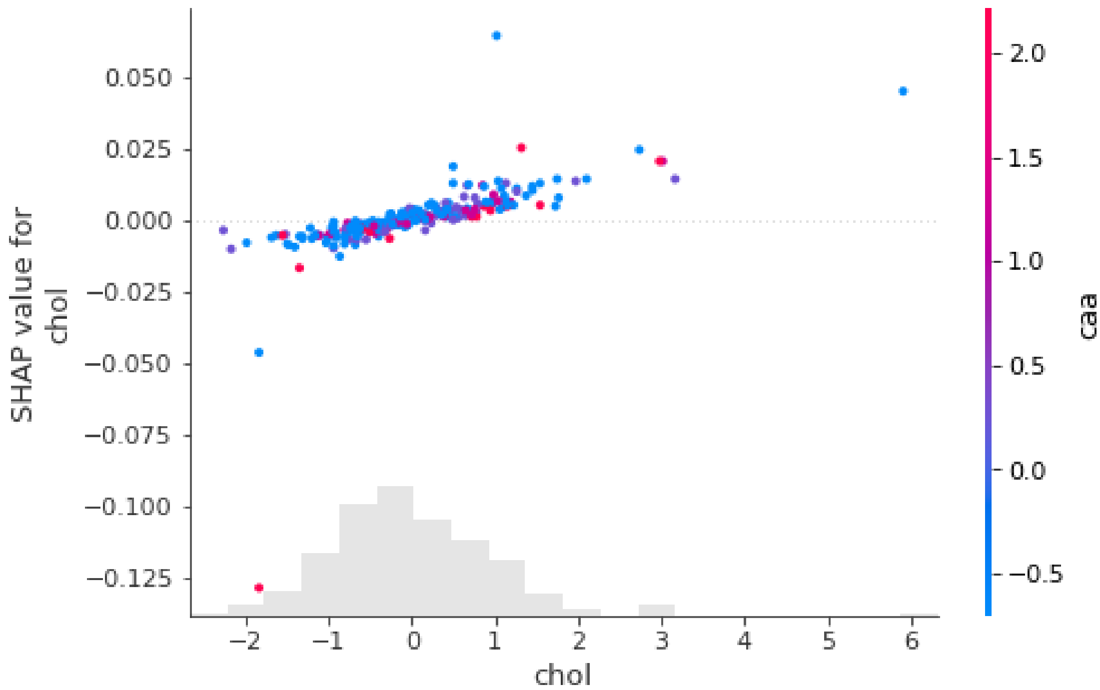
```
Printing Scatter SHAP Plot Between Features:
```

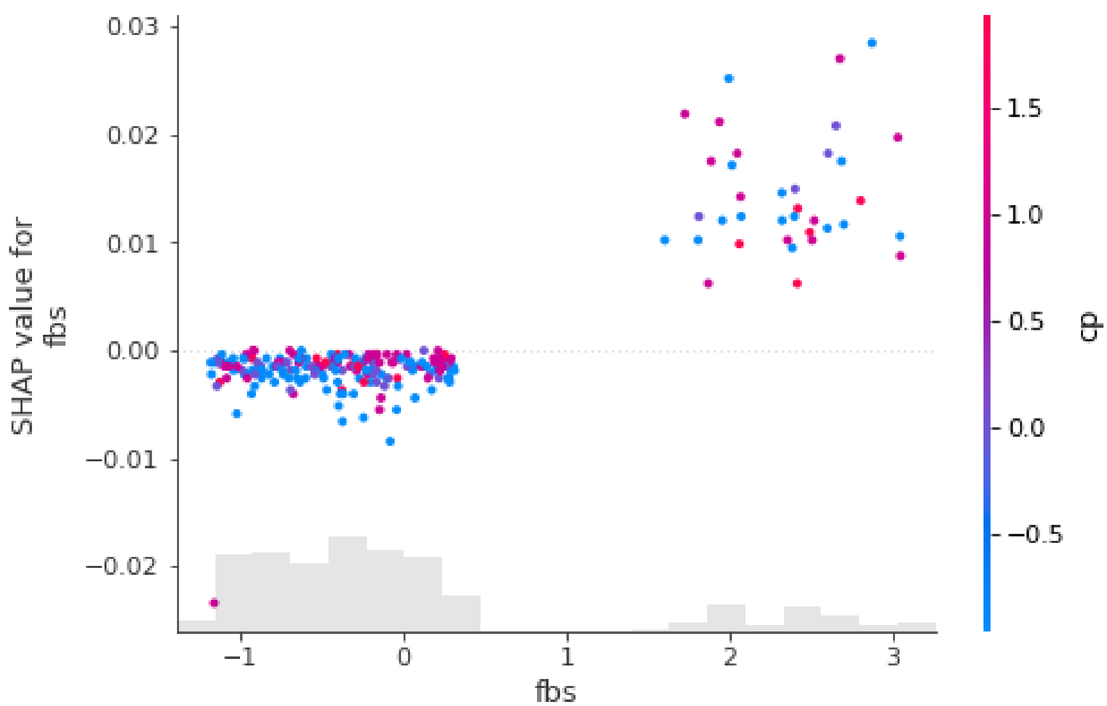


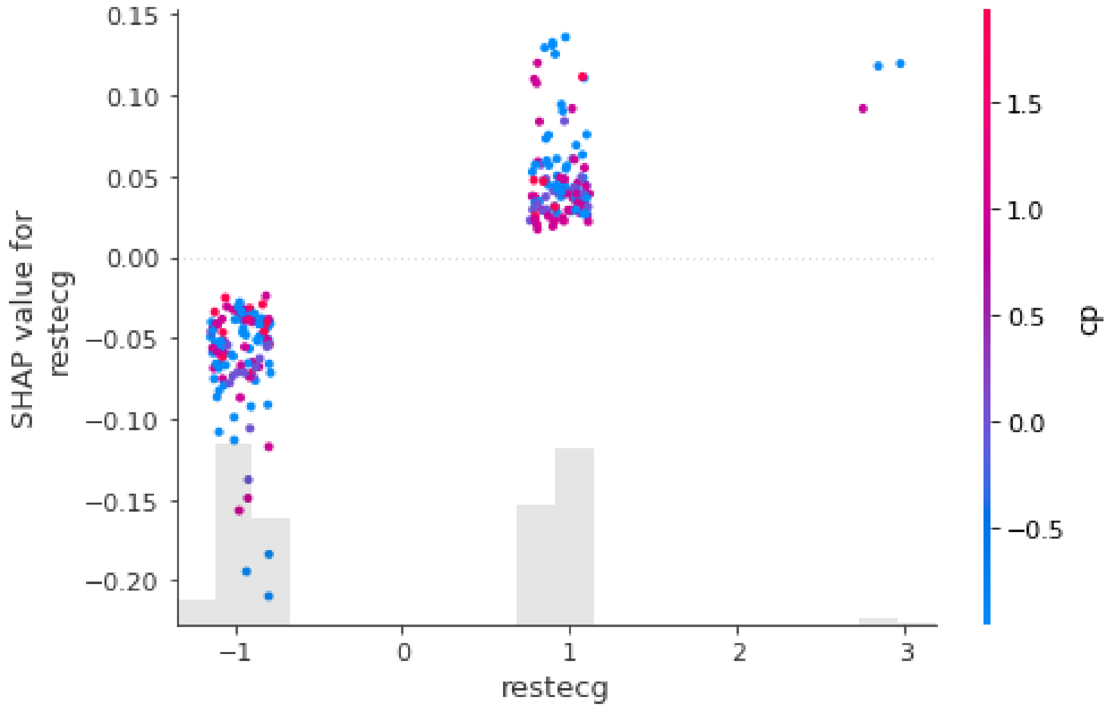


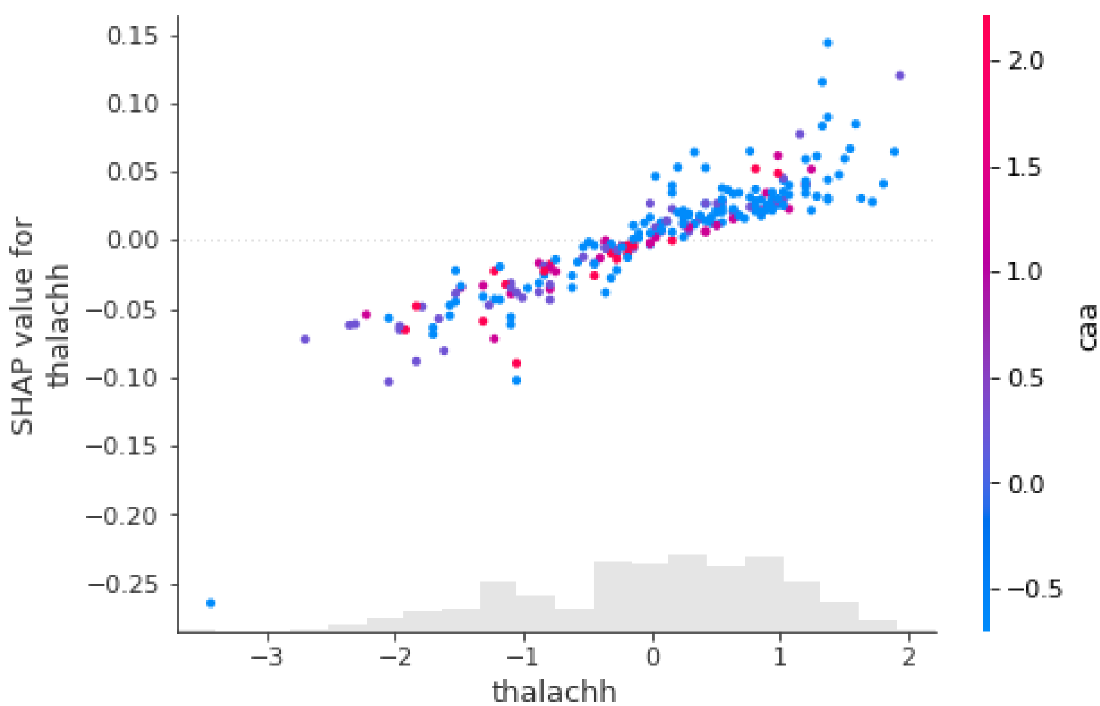

SHAP value for cp
cp
exng
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50

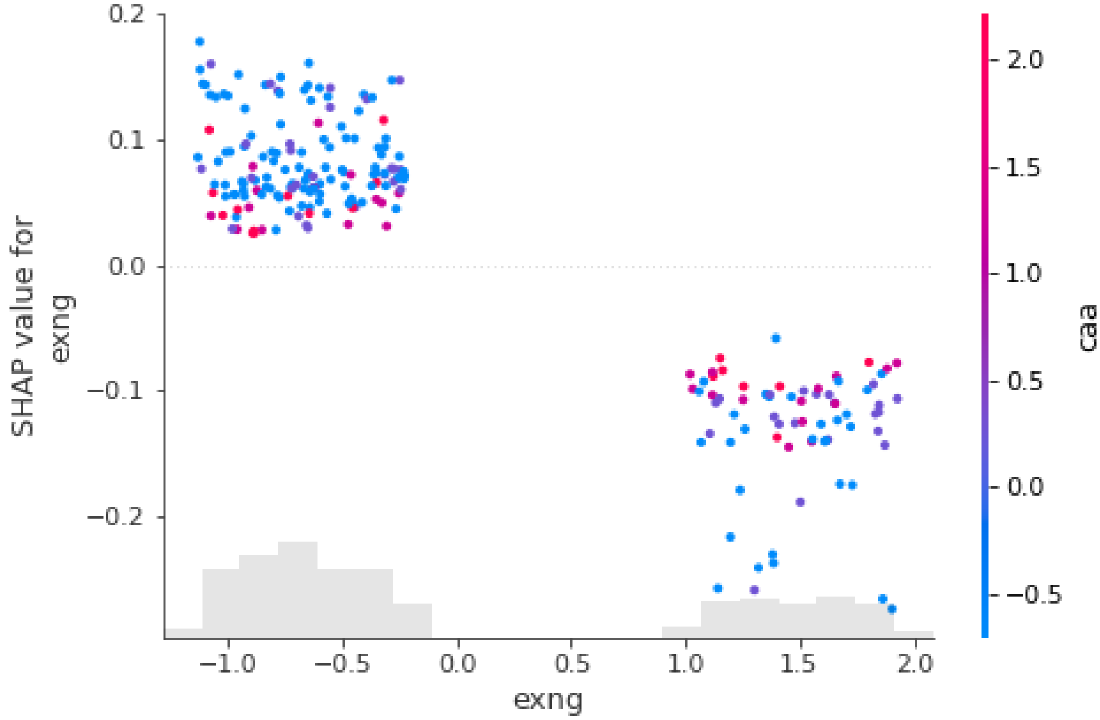

SHAP value for trtbps
trtbps
sex
0.2
0.1
0.0
−0.1
−0.2
−0.3
−2
−1
0
1
2
3
4
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25


SHAP value for chol
chol
caa
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−2
−1
0
1
2
3
4
5
6
2.0
1.5
1.0
0.5
0.0
−0.5

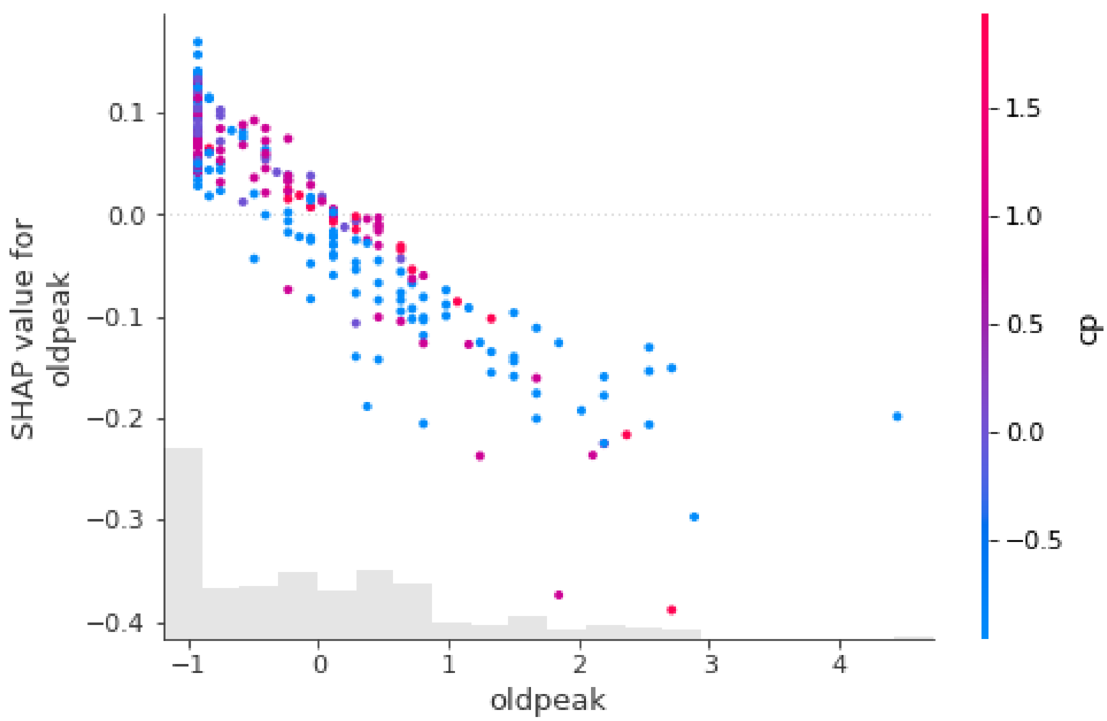

SHAP value for fbs
fbs
cp
0.03
0.02
0.01
0.00
−0.01
−0.02
−1
0
1
2
3
1.5
1.0
0.5
0.0
−0.5


0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
SHAP value for restecg
−1
0
1
2
3
restecg
1.5
1.0
0.5
0.0
−0.5
cp

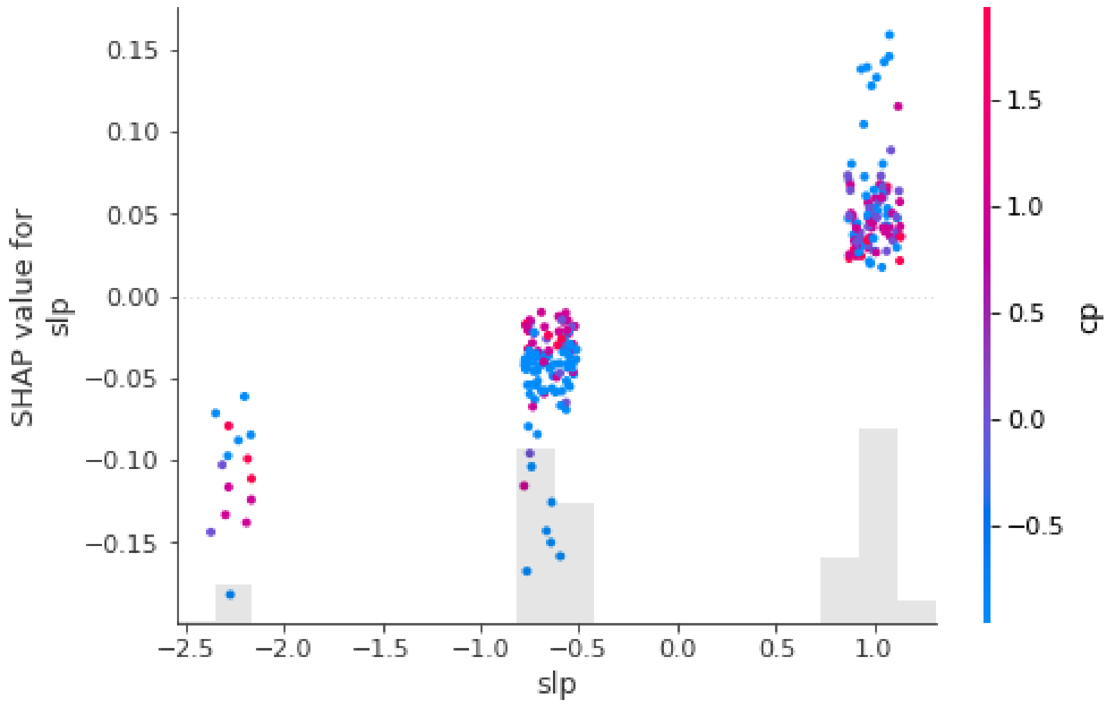

0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
SHAP value for thalachh
−3
−2
−1
0
1
2
thalachh
2.0
1.5
1.0
0.5
0.0
−0.5
caa

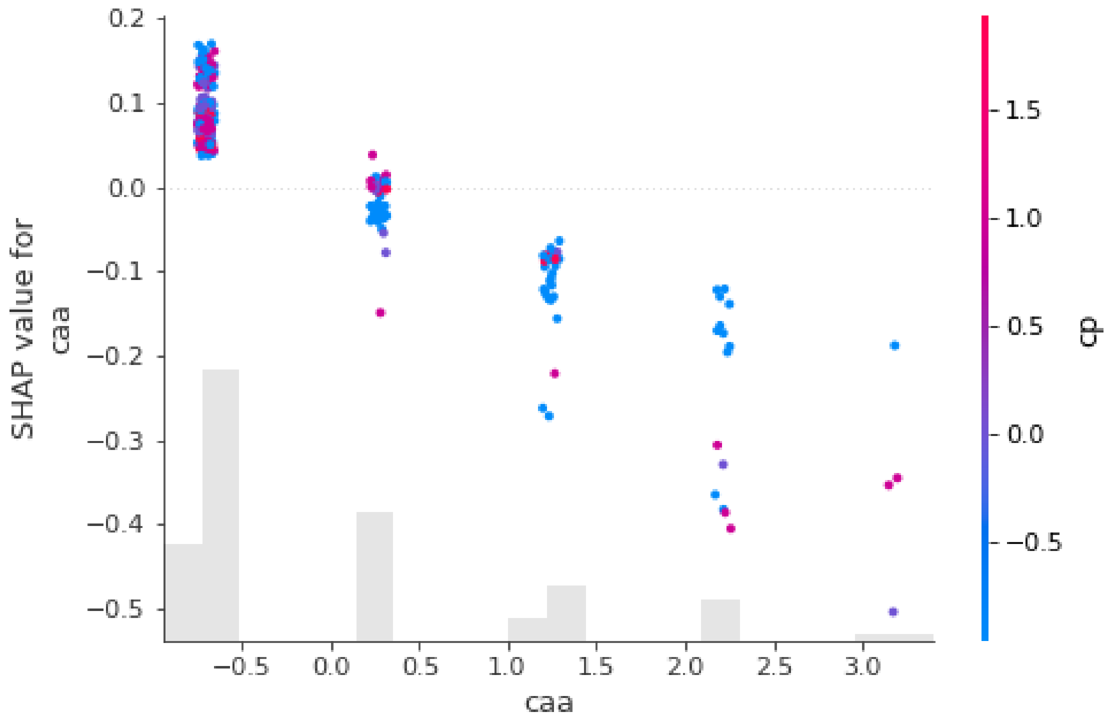


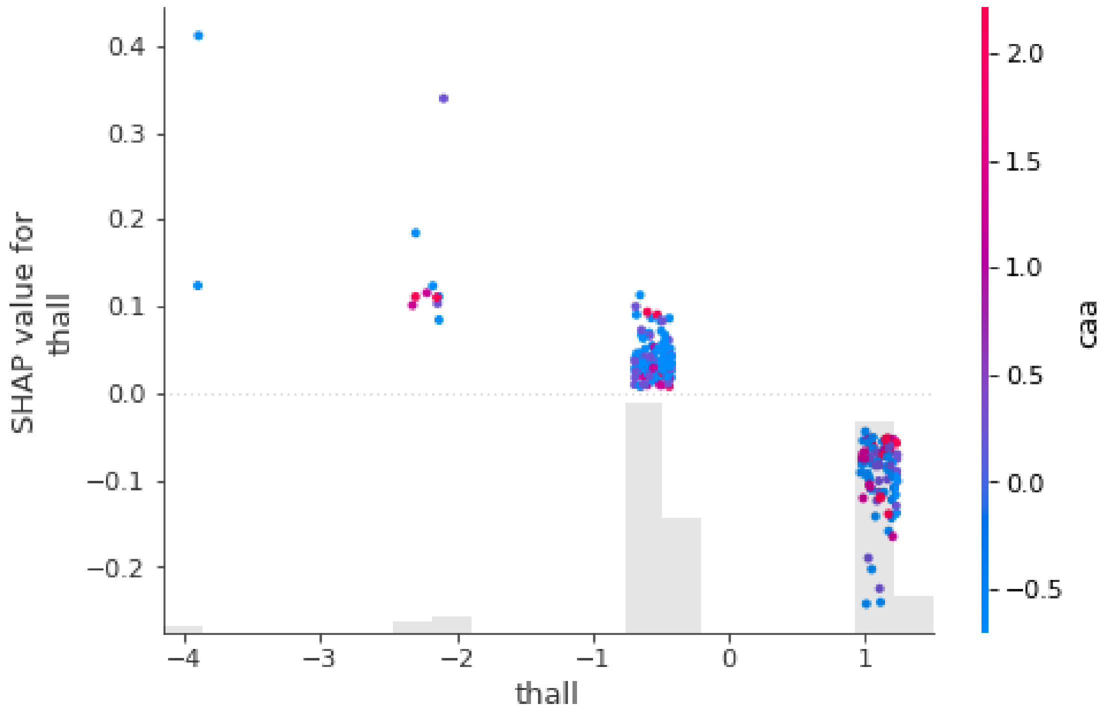
SHAP value for exng
exng
caa



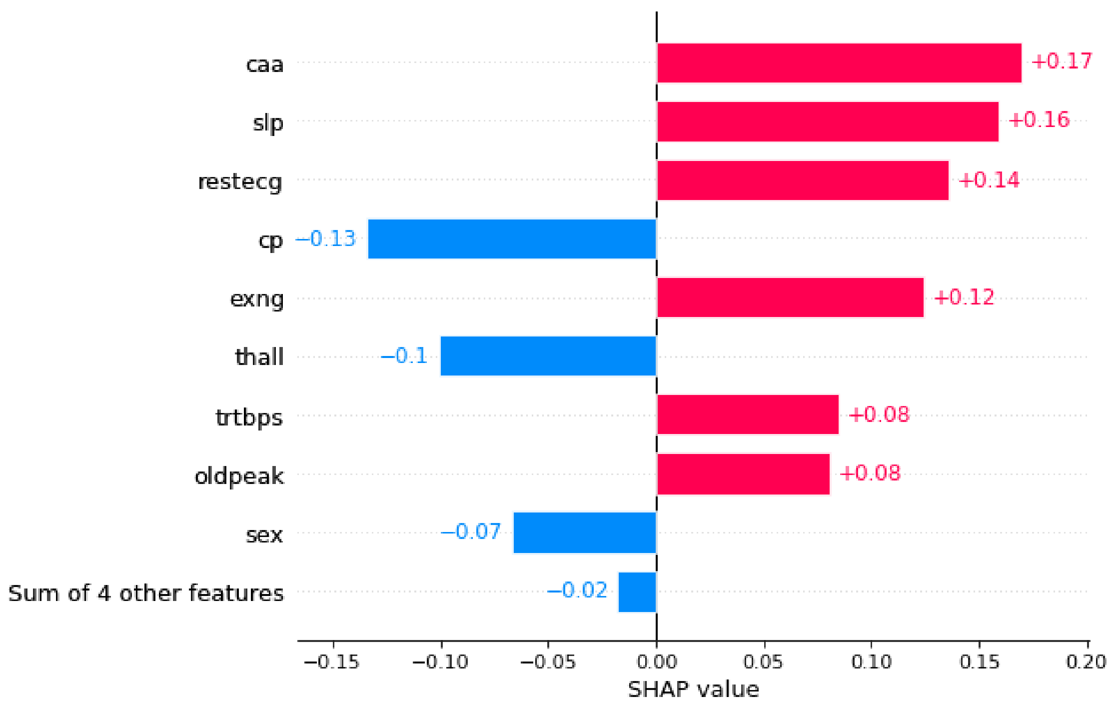
SHAP value for oldpeak
oldpeak
cp


SHAP value for slp
slp
cp
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
0.5
−0.5

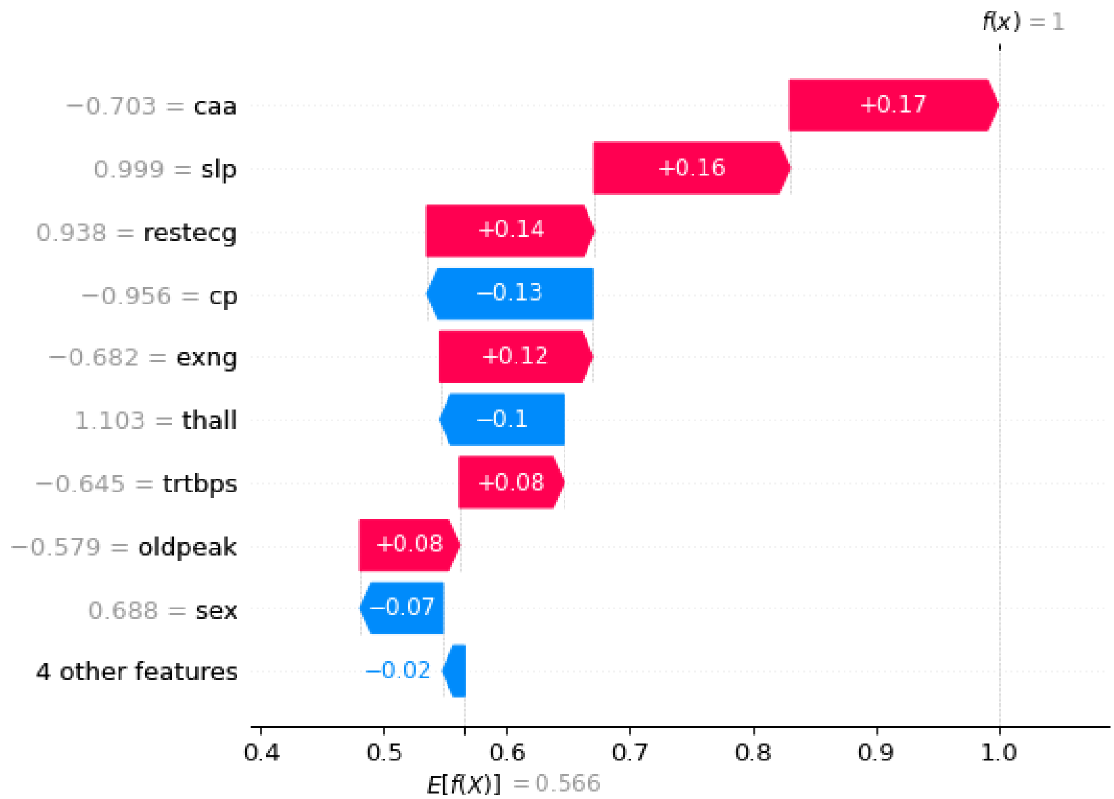

SHAP value for caa
caa
cp
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
0.5
1.0
1.5
2.0
2.5
3.0
−0.5




```
Printing Bar SHAP Plot for Local, Instance-Wise Effects:
```



Printing Waterfall SHAP Plot for Local, Instance-Wise Effects:



Printing Force SHAP Plot for Local, Instance-Wise Effects:

[11]: <shap.plots._force.AdditiveForceVisualizer at 0x12b874c10>

[12]:
```
# References to put code together, compile, and test run of a Logistic␣
↪Regression model using SHAP
#           Splitting CSV Into Trainand Test Data by Nishank Sharma: https://
↪medium.com/themlblog/splitting-csv-into-train-and-test-data-1407a063dd74
#           Logistic Regression in Python by Mirko Stojiljkovic: https://
↪realpython.com/logistic-regression-python/
#           How to interpret machine learning (ML) models with SHAP values by␣
↪Xiaoyou Wang: https://www.mage.ai/blog/
↪how-to-interpret-explain-machine-learning-models-using-shap-values
```

```
#           SHAP explainer and models: https://www.mage.ai/blog/
↪how-to-interpret-explain-machine-learning-models-using-shap-values
#           Dataset taken from: https://www.kaggle.com/datasets/
↪rashikrahmanpritom/heart-attack-analysis-prediction-dataset?resource=download
#           scikit learn: https://scikit-learn.org/stable/modules/generated/
↪sklearn.preprocessing.StandardScaler.html
#           SHAP Force Plots for Classification by Max Steele: https://medium.
↪com/mlearning-ai/shap-force-plots-for-classification-d30be430e195
#           Machine Learning - Logistic Regression with Python by Nikhil␣
↪Adithyan: https://medium.com/codex/
↪machine-learning-logistic-regression-with-python-5ed4ded9d146
```