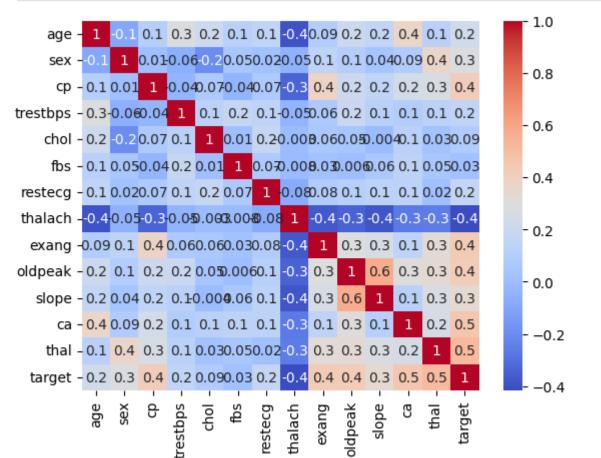
```
In [ ]: # Tyler Boudreau
        # Import Required packages as needed throughout
        import pandas as pd
        import numpy as np
        import seaborn as sb
        import matplotlib.pyplot as plt
        # Location of Dataset must be set
        df = pd.read_csv('C:\\Users\\Tyler\\Downloads\\Heart_disease_cleveland_new.csv')
        print(df)
        df.head(10)
            age sex cp trestbps chol fbs
                                               restecg thalach exang oldpeak
       0
             63
                   1
                       0
                               145
                                     233
                                            1
                                                      2
                                                             150
                                                                      0
                                                                             2.3
                                                                                  \
                      3
                                                      2
       1
             67
                   1
                               160
                                     286
                                                             108
                                                                      1
                                                                             1.5
       2
             67
                   1 3
                               120
                                     229
                                                      2
                                                             129
                                                                      1
                                                                             2.6
                                            0
       3
             37
                   1
                       2
                               130
                                     250
                                            0
                                                     0
                                                             187
                                                                      0
                                                                             3.5
             41
       4
                   0
                       1
                               130
                                     204
                                            0
                                                      2
                                                             172
                                                                      0
                                                                             1.4
                               . . .
                                                                             . . .
            . . .
                 . . .
                      . .
                                     . . .
                                                    . . .
                                                             . . .
                                                                    . . .
       . .
                                          . . .
       298
             45
                 1 0
                               110
                                     264
                                          0
                                                     0
                                                             132
                                                                      0
                                                                             1.2
       299
                       3
                               144
                                     193
                                                     0
                                                             141
                                                                      0
                                                                             3.4
             68
                   1
                                            1
                   1 3
                                                                             1.2
       300
             57
                               130
                                     131
                                            0
                                                     0
                                                             115
                                                                      1
       301
             57
                   0
                       1
                               130
                                     236
                                            0
                                                     2
                                                             174
                                                                      0
                                                                             0.0
       302
             38
                       2
                               138
                                     175
                                                     0
                                                             173
                                                                             0.0
                   1
                                            0
                                                                      0
            slope ca thal target
                2
       0
                    0
                          2
       1
                1
                    3
                          1
                                  1
                    2
       2
                1
                          3
                                  1
       3
                2
                    0
                          1
                                  0
       4
                0
                    0
                          1
                                  0
              . . .
                   . .
       298
                1
                    0
                          3
                                  1
       299
                    2
                          3
                1
                                  1
       300
                1
                    1
                          3
                                  1
```

[303 rows x 14 columns]

Out[]:		age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	ti
	0	63	1	0	145	233	1	2	150	0	2.3	2	0	2	
	1	67	1	3	160	286	0	2	108	1	1.5	1	3	1	
	2	67	1	3	120	229	0	2	129	1	2.6	1	2	3	
	3	37	1	2	130	250	0	0	187	0	3.5	2	0	1	
	4	41	0	1	130	204	0	2	172	0	1.4	0	0	1	
	5	56	1	1	120	236	0	0	178	0	0.8	0	0	1	
	6	62	0	3	140	268	0	2	160	0	3.6	2	2	1	
	7	57	0	3	120	354	0	0	163	1	0.6	0	0	1	
	8	63	1	3	130	254	0	2	147	0	1.4	1	1	3	
	۵	E 2	1	2	140	202	1	າ	155	1	2 1	າ	Λ	2	



```
In [ ]: X=df.iloc[:,0:13]
       y=df['target']
       # Create Supervised Train and Unsupervised Test Partitions
       from sklearn.model_selection import train_test_split
       X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.33, random_state
       # Count number 0 and 1 prediction values for Heart Disease, 0 being absent, 1 being
       y.value_counts()
Out[]: target
           139
       Name: count, dtype: int64
In [ ]: # Logistic Regression Model
       from sklearn.linear_model import LogisticRegression
       logModel=LogisticRegression(max_iter=10000)
       logModel.fit(X_train, y_train)
       pred_y = logModel.predict(X_test)
       from sklearn.metrics import accuracy_score
       print('Logistic Regression Model Accuracy: {0:0.4f}'.format(accuracy_score(y_test,p
       predresult1 = pd.DataFrame({"Actual" : y_test, "Predicted" : pred_y})
       print(predresult1)
      Logistic Regression Model Accuracy: 81.0000 %
          Actual Predicted
      166
             0
      182
      292
             1
      22
             1
      179
             0
                       1
      41
             0
                      0
      282
             1
      200
      174
              1
                       1
      18
              a
                        a
      [100 rows x 2 columns]
In [ ]: # Testing Logistic Regression model on example data
       Logmodelprediction1 = logModel.predict(XTestValues1)
       Logmodelprediction2 = logModel.predict(XTestValues2)
       print(Logmodelprediction1)
       print(Logmodelprediction2)
      [0]
      [1]
In [ ]: # LightGBM Model
       import lightgbm as lgb
       clf = lgb.LGBMClassifier()
```

```
clf.fit(X train, y train)
        y_pred=clf.predict(X_test)
        accuracy=accuracy_score(y_pred, y_test)
        print('LightGBM Model Accuracy: {0:0.4f}'.format(accuracy_score(y_test, y_pred)*100
        predresult2 = pd.DataFrame({"Actual" : y_test, "Predicted" : y_pred})
        print(predresult2)
        LightGBMPred1 = clf.predict(XTestValues1)
        LightGBMPred2 = clf.predict(XTestValues2)
        print(LightGBMPred1)
        print(LightGBMPred2)
      LightGBM Model Accuracy: 76.0000 %
           Actual Predicted
            0
      166
      182
              0
                         1
                        1
      292
              1
      22
              1
      179
             0
            0
            . . .
                       . . .
      41
                         0
                      0
      282
              1
      200
              0
      174
              1
           0
      18
      [100 rows x 2 columns]
      [0]
      [1]
In [ ]: # Random Forest Model
       from sklearn.ensemble import RandomForestClassifier
        clf = RandomForestClassifier(n_estimators = 100)
        # Training the model on the training dataset
        # fit function is used to train the model using the training sets as parameters
        clf.fit(X_train, y_train)
        # performing predictions on the test dataset
        y_pred8 = clf.predict(X_test)
        # metrics are used to find accuracy or error
        from sklearn import metrics
        print()
        # using metrics module for accuracy calculation
        print("Random Forest Accuracy:",metrics.accuracy_score(y_test, y_pred8)*100,"%")
        predresult3 = pd.DataFrame({"Actual" : y_test, "Predicted" : y_pred8})
        print(predresult3)
        RandomForestPred1 = clf.predict(XTestValues1)
        RandomForestPred2 = clf.predict(XTestValues2)
        print(RandomForestPred1)
        print(RandomForestPred2)
```

```
Random Forest Accuracy: 83.0 %
       Actual Predicted
     166 0 0
                      0
      182
            0
      292
             1
                      1
             1
      22
                       0
     22 1
179 0
                      1
     1.
41 0
                     0
                      1
     200
            0
                      0
     174
             1
                      1
     18 0
      [100 rows x 2 columns]
      [0]
     [1]
In [ ]: # ExtraTree Model
       from sklearn.ensemble import ExtraTreesClassifier
       clf = ExtraTreesClassifier(n_estimators=100,max_depth=6,min_samples_split=2,min_wei
       clf.fit(X_train, y_train)
       print("ExtraTree Classifier Accuracy:",clf.score(X_test, y_test)*100,"%")
       y_pred9 = clf.predict(X_test)
       predresult4 = pd.DataFrame({"Actual" : y_test, "Predicted" : y_pred9})
       print(predresult4)
       ExtraTreePred1 = clf.predict(XTestValues1)
       ExtraTreePred2 = clf.predict(XTestValues2)
       print(ExtraTreePred1)
       print(ExtraTreePred2)
      ExtraTree Classifier Accuracy: 83.0 %
         Actual Predicted
      166 0 0
      182
            0
     292
22
                      1
             1
             1
                      0
     179
            0
                      1
     ••
           . . .
                    . . .
           0
           1
      282
                      1
      200
            0
                      0
     174
             1
                      1
      18 0
      [100 rows x 2 columns]
      [0]
      [1]
In [ ]: # XGBoost Model
       from xgboost import XGBClassifier
       from sklearn.metrics import accuracy_score
       model = XGBClassifier(eval_metric='mlogloss')
       model.fit(X_train, y_train)
       y_pred1 = model.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred1)
        print("XGBoost Accuracy:",accuracy*100,"%")
        predresult5 = pd.DataFrame({"Actual" : y_test, "Predicted" : y_pred1})
        print(predresult5)
        XGBoostPred1 = model.predict(XTestValues1)
        XGBoostPred2 = model.predict(XTestValues2)
        print(XGBoostPred1)
        print(XGBoostPred2)
      XGBoost Accuracy: 78.0 %
           Actual Predicted
      166
      182
               0
                         1
               1
      292
               1
      22
      179
              0
                         1
                       . . .
      . .
            . . .
      41
              0
              1
      282
      200
              0
                         1
              1
      174
              0
      18
      [100 rows x 2 columns]
      [0]
      [1]
In [ ]: # Setup TensorFLow Model
        from tensorflow.keras.models import Sequential #Helps to create Forward and backwar
        from tensorflow.keras.layers import Dense #Helps to create neurons in ANN
In [ ]: # Continue TensorFlow Setup
        classifier=Sequential()
        classifier.add(Dense(units=11,activation='relu'))
        classifier.add(Dense(units=7,activation='relu'))
        classifier.add(Dense(units=6,activation='relu'))
        ## Adding the output layer
        classifier.add(Dense(units=1,activation='sigmoid'))
        classifier.compile(optimizer='adam',loss="binary_crossentropy",metrics=["accuracy"]
        #classifier.compile(optimizer=opt,loss="binary_crossentropy",metrics=["accuracy"])
In [ ]: # TensorFlow continued setup
        import tensorflow as tf
        early_stopping=tf.keras.callbacks.EarlyStopping(
            monitor="val_loss",
            min_delta=0.0001,
            patience=20,
            verbose=1,
            mode="auto",
            baseline=None,
            restore_best_weights=False,
In [ ]: # Runs TensorFlow model up to 1000 iterations or until optimal value is found
```

model_history=classifier.fit(X_train,y_train,validation_split=0.30,batch_size=10,ep

```
Epoch 1/1000
141 - val loss: 2.8482 - val accuracy: 0.5410
Epoch 2/1000
41 - val_loss: 1.8760 - val_accuracy: 0.5410
Epoch 3/1000
30 - val_loss: 1.1076 - val_accuracy: 0.5738
Epoch 4/1000
25 - val_loss: 0.9665 - val_accuracy: 0.4754
Epoch 5/1000
89 - val_loss: 1.0543 - val_accuracy: 0.5410
Epoch 6/1000
04 - val_loss: 0.9074 - val_accuracy: 0.5082
Epoch 7/1000
15/15 [=============] - 0s 6ms/step - loss: 0.7892 - accuracy: 0.58
45 - val_loss: 0.8317 - val_accuracy: 0.5082
Epoch 8/1000
75 - val_loss: 0.7986 - val_accuracy: 0.5082
Epoch 9/1000
97 - val_loss: 0.7534 - val_accuracy: 0.5574
Epoch 10/1000
68 - val_loss: 0.7228 - val_accuracy: 0.5738
Epoch 11/1000
15/15 [=============] - 0s 7ms/step - loss: 0.6943 - accuracy: 0.62
68 - val_loss: 0.7220 - val_accuracy: 0.5738
Epoch 12/1000
79 - val_loss: 0.7189 - val_accuracy: 0.5574
08 - val_loss: 0.7097 - val_accuracy: 0.5902
Epoch 14/1000
97 - val_loss: 0.6983 - val_accuracy: 0.5738
Epoch 15/1000
68 - val_loss: 0.7021 - val_accuracy: 0.5738
Epoch 16/1000
15/15 [=============] - 0s 6ms/step - loss: 0.6753 - accuracy: 0.64
08 - val_loss: 0.7075 - val_accuracy: 0.5738
Epoch 17/1000
68 - val_loss: 0.7031 - val_accuracy: 0.5902
Epoch 18/1000
38 - val_loss: 0.7048 - val_accuracy: 0.5738
Epoch 19/1000
```

```
38 - val_loss: 0.6967 - val_accuracy: 0.5738
Epoch 20/1000
68 - val_loss: 0.7070 - val_accuracy: 0.5902
Epoch 21/1000
38 - val loss: 0.6965 - val accuracy: 0.5738
Epoch 22/1000
38 - val_loss: 0.7033 - val_accuracy: 0.5738
Epoch 23/1000
38 - val_loss: 0.7101 - val_accuracy: 0.5574
Epoch 24/1000
38 - val_loss: 0.7034 - val_accuracy: 0.5738
Epoch 25/1000
38 - val loss: 0.7038 - val accuracy: 0.5738
Epoch 26/1000
97 - val_loss: 0.6983 - val_accuracy: 0.5902
Epoch 27/1000
08 - val_loss: 0.7142 - val_accuracy: 0.5246
Epoch 28/1000
79 - val_loss: 0.6951 - val_accuracy: 0.5902
Epoch 29/1000
97 - val loss: 0.6927 - val accuracy: 0.5738
Epoch 30/1000
38 - val_loss: 0.6936 - val_accuracy: 0.5738
Epoch 31/1000
08 - val_loss: 0.6952 - val_accuracy: 0.5738
Epoch 32/1000
68 - val_loss: 0.7020 - val_accuracy: 0.5902
Epoch 33/1000
08 - val_loss: 0.6966 - val_accuracy: 0.5738
Epoch 34/1000
08 - val_loss: 0.7103 - val_accuracy: 0.5902
79 - val_loss: 0.6889 - val_accuracy: 0.5738
Epoch 36/1000
08 - val_loss: 0.6984 - val_accuracy: 0.5902
Epoch 37/1000
08 - val_loss: 0.6960 - val_accuracy: 0.5738
Epoch 38/1000
```

```
38 - val_loss: 0.6955 - val_accuracy: 0.5738
Epoch 39/1000
15/15 [=============] - 0s 6ms/step - loss: 0.6278 - accuracy: 0.63
38 - val_loss: 0.6965 - val_accuracy: 0.5738
Epoch 40/1000
79 - val_loss: 0.6901 - val_accuracy: 0.5574
Epoch 41/1000
08 - val_loss: 0.6903 - val_accuracy: 0.5574
Epoch 42/1000
38 - val_loss: 0.6942 - val_accuracy: 0.5574
Epoch 43/1000
20 - val_loss: 0.6905 - val_accuracy: 0.5738
Epoch 44/1000
79 - val_loss: 0.6869 - val_accuracy: 0.5246
Epoch 45/1000
08 - val_loss: 0.6858 - val_accuracy: 0.5410
Epoch 46/1000
79 - val_loss: 0.6867 - val_accuracy: 0.5410
Epoch 47/1000
79 - val_loss: 0.6868 - val_accuracy: 0.5574
Epoch 48/1000
20 - val_loss: 0.6874 - val_accuracy: 0.5246
Epoch 49/1000
20 - val_loss: 0.6906 - val_accuracy: 0.5902
Epoch 50/1000
49 - val_loss: 0.6938 - val_accuracy: 0.5902
Epoch 51/1000
49 - val loss: 0.6825 - val accuracy: 0.5902
61 - val_loss: 0.6918 - val_accuracy: 0.5574
Epoch 53/1000
20 - val_loss: 0.6798 - val_accuracy: 0.6066
Epoch 54/1000
61 - val_loss: 0.6799 - val_accuracy: 0.5574
Epoch 55/1000
49 - val_loss: 0.6763 - val_accuracy: 0.5738
Epoch 56/1000
20 - val_loss: 0.6818 - val_accuracy: 0.6066
```

```
Epoch 57/1000
61 - val_loss: 0.6804 - val_accuracy: 0.5738
Epoch 58/1000
20 - val_loss: 0.6804 - val_accuracy: 0.5738
Epoch 59/1000
20 - val_loss: 0.6792 - val_accuracy: 0.5246
Epoch 60/1000
31 - val_loss: 0.6823 - val_accuracy: 0.5738
Epoch 61/1000
31 - val_loss: 0.6796 - val_accuracy: 0.5738
Epoch 62/1000
01 - val_loss: 0.6725 - val_accuracy: 0.6230
Epoch 63/1000
15/15 [=============] - 0s 6ms/step - loss: 0.5790 - accuracy: 0.67
61 - val_loss: 0.6758 - val_accuracy: 0.5738
Epoch 64/1000
20 - val_loss: 0.6725 - val_accuracy: 0.5738
Epoch 65/1000
90 - val_loss: 0.6712 - val_accuracy: 0.5902
Epoch 66/1000
61 - val_loss: 0.6686 - val_accuracy: 0.5902
Epoch 67/1000
15/15 [============] - 0s 6ms/step - loss: 0.5671 - accuracy: 0.68
31 - val_loss: 0.6643 - val_accuracy: 0.5902
Epoch 68/1000
31 - val_loss: 0.6610 - val_accuracy: 0.6230
Epoch 69/1000
54 - val_loss: 0.6769 - val_accuracy: 0.6066
Epoch 70/1000
61 - val_loss: 0.6655 - val_accuracy: 0.6066
Epoch 71/1000
31 - val_loss: 0.6574 - val_accuracy: 0.6066
Epoch 72/1000
15/15 [=============] - 0s 8ms/step - loss: 0.5741 - accuracy: 0.67
61 - val_loss: 0.6561 - val_accuracy: 0.6066
Epoch 73/1000
61 - val_loss: 0.6619 - val_accuracy: 0.6230
Epoch 74/1000
01 - val_loss: 0.6482 - val_accuracy: 0.6230
Epoch 75/1000
```

```
72 - val_loss: 0.6452 - val_accuracy: 0.5902
Epoch 76/1000
13 - val_loss: 0.6454 - val_accuracy: 0.6557
Epoch 77/1000
42 - val loss: 0.6465 - val accuracy: 0.6393
Epoch 78/1000
13 - val_loss: 0.6440 - val_accuracy: 0.6393
Epoch 79/1000
13 - val_loss: 0.6434 - val_accuracy: 0.6557
Epoch 80/1000
72 - val_loss: 0.6429 - val_accuracy: 0.6393
Epoch 81/1000
83 - val_loss: 0.6427 - val_accuracy: 0.6230
Epoch 82/1000
13 - val_loss: 0.6376 - val_accuracy: 0.6393
Epoch 83/1000
83 - val_loss: 0.6436 - val_accuracy: 0.6393
Epoch 84/1000
42 - val_loss: 0.6350 - val_accuracy: 0.6557
Epoch 85/1000
42 - val_loss: 0.6361 - val_accuracy: 0.6557
Epoch 86/1000
01 - val_loss: 0.6264 - val_accuracy: 0.6230
Epoch 87/1000
54 - val_loss: 0.6299 - val_accuracy: 0.6885
Epoch 88/1000
94 - val_loss: 0.6306 - val_accuracy: 0.6557
Epoch 89/1000
42 - val_loss: 0.6336 - val_accuracy: 0.6557
Epoch 90/1000
83 - val_loss: 0.6238 - val_accuracy: 0.6885
Epoch 91/1000
24 - val_loss: 0.6255 - val_accuracy: 0.6721
Epoch 92/1000
83 - val_loss: 0.6208 - val_accuracy: 0.6885
Epoch 93/1000
83 - val_loss: 0.6167 - val_accuracy: 0.6230
Epoch 94/1000
```

```
24 - val_loss: 0.6175 - val_accuracy: 0.6885
Epoch 95/1000
15/15 [=============] - 0s 6ms/step - loss: 0.5427 - accuracy: 0.73
24 - val_loss: 0.6179 - val_accuracy: 0.6885
Epoch 96/1000
83 - val_loss: 0.6174 - val_accuracy: 0.6885
Epoch 97/1000
72 - val_loss: 0.6190 - val_accuracy: 0.6885
Epoch 98/1000
54 - val_loss: 0.6075 - val_accuracy: 0.6393
Epoch 99/1000
65 - val_loss: 0.6153 - val_accuracy: 0.6885
Epoch 100/1000
94 - val_loss: 0.6077 - val_accuracy: 0.6885
Epoch 101/1000
94 - val_loss: 0.6048 - val_accuracy: 0.7213
Epoch 102/1000
13 - val_loss: 0.6094 - val_accuracy: 0.6885
Epoch 103/1000
65 - val_loss: 0.6049 - val_accuracy: 0.6885
Epoch 104/1000
54 - val_loss: 0.6025 - val_accuracy: 0.6885
Epoch 105/1000
42 - val_loss: 0.6065 - val_accuracy: 0.6885
Epoch 106/1000
35 - val_loss: 0.5962 - val_accuracy: 0.7213
Epoch 107/1000
35 - val loss: 0.6118 - val accuracy: 0.7049
Epoch 108/1000
54 - val_loss: 0.5977 - val_accuracy: 0.7049
Epoch 109/1000
54 - val_loss: 0.5955 - val_accuracy: 0.7049
Epoch 110/1000
54 - val_loss: 0.5965 - val_accuracy: 0.6885
Epoch 111/1000
54 - val_loss: 0.5886 - val_accuracy: 0.7213
Epoch 112/1000
65 - val_loss: 0.6007 - val_accuracy: 0.7213
```

```
Epoch 113/1000
42 - val loss: 0.5859 - val accuracy: 0.7049
Epoch 114/1000
35 - val_loss: 0.5889 - val_accuracy: 0.7049
Epoch 115/1000
24 - val_loss: 0.5829 - val_accuracy: 0.7213
Epoch 116/1000
46 - val_loss: 0.5919 - val_accuracy: 0.7213
Epoch 117/1000
65 - val_loss: 0.5794 - val_accuracy: 0.7377
Epoch 118/1000
24 - val_loss: 0.5875 - val_accuracy: 0.7377
Epoch 119/1000
15/15 [==============] - 0s 6ms/step - loss: 0.5144 - accuracy: 0.74
65 - val_loss: 0.5794 - val_accuracy: 0.7049
Epoch 120/1000
42 - val_loss: 0.5759 - val_accuracy: 0.7377
Epoch 121/1000
35 - val_loss: 0.5781 - val_accuracy: 0.7049
Epoch 122/1000
06 - val_loss: 0.5710 - val_accuracy: 0.7377
Epoch 123/1000
06 - val_loss: 0.5785 - val_accuracy: 0.7213
Epoch 124/1000
35 - val_loss: 0.5700 - val_accuracy: 0.7377
Epoch 125/1000
65 - val_loss: 0.5737 - val_accuracy: 0.7213
Epoch 126/1000
35 - val_loss: 0.5636 - val_accuracy: 0.7213
Epoch 127/1000
06 - val_loss: 0.5702 - val_accuracy: 0.7213
Epoch 128/1000
15/15 [=============] - 0s 6ms/step - loss: 0.4899 - accuracy: 0.75
35 - val_loss: 0.5730 - val_accuracy: 0.7541
Epoch 129/1000
46 - val_loss: 0.5594 - val_accuracy: 0.7377
Epoch 130/1000
65 - val_loss: 0.5632 - val_accuracy: 0.7377
Epoch 131/1000
```

```
17 - val_loss: 0.5623 - val_accuracy: 0.7377
Epoch 132/1000
06 - val_loss: 0.5597 - val_accuracy: 0.7377
Epoch 133/1000
46 - val loss: 0.5585 - val accuracy: 0.7377
Epoch 134/1000
46 - val_loss: 0.5566 - val_accuracy: 0.7377
Epoch 135/1000
06 - val_loss: 0.5635 - val_accuracy: 0.7541
Epoch 136/1000
06 - val_loss: 0.5503 - val_accuracy: 0.7377
Epoch 137/1000
17 - val loss: 0.5473 - val accuracy: 0.7377
Epoch 138/1000
76 - val_loss: 0.5665 - val_accuracy: 0.7705
Epoch 139/1000
06 - val_loss: 0.5424 - val_accuracy: 0.7541
Epoch 140/1000
76 - val_loss: 0.5452 - val_accuracy: 0.7541
Epoch 141/1000
87 - val_loss: 0.5527 - val_accuracy: 0.7869
Epoch 142/1000
76 - val_loss: 0.5450 - val_accuracy: 0.7541
Epoch 143/1000
17 - val_loss: 0.5382 - val_accuracy: 0.7705
Epoch 144/1000
76 - val_loss: 0.5341 - val_accuracy: 0.7541
Epoch 145/1000
58 - val_loss: 0.5318 - val_accuracy: 0.7541
Epoch 146/1000
35 - val_loss: 0.5423 - val_accuracy: 0.7869
Epoch 147/1000
17 - val_loss: 0.5304 - val_accuracy: 0.8033
Epoch 148/1000
87 - val_loss: 0.5314 - val_accuracy: 0.7705
Epoch 149/1000
46 - val_loss: 0.5304 - val_accuracy: 0.7541
Epoch 150/1000
```

```
87 - val_loss: 0.5237 - val_accuracy: 0.8033
Epoch 151/1000
17 - val_loss: 0.5207 - val_accuracy: 0.7705
Epoch 152/1000
87 - val_loss: 0.5264 - val_accuracy: 0.7541
Epoch 153/1000
46 - val_loss: 0.5175 - val_accuracy: 0.7541
Epoch 154/1000
76 - val_loss: 0.5221 - val_accuracy: 0.7541
Epoch 155/1000
28 - val_loss: 0.5169 - val_accuracy: 0.8033
Epoch 156/1000
17 - val_loss: 0.5144 - val_accuracy: 0.8033
Epoch 157/1000
58 - val_loss: 0.5193 - val_accuracy: 0.7705
Epoch 158/1000
17 - val_loss: 0.5087 - val_accuracy: 0.7705
Epoch 159/1000
69 - val_loss: 0.5090 - val_accuracy: 0.8033
Epoch 160/1000
17 - val_loss: 0.5158 - val_accuracy: 0.7869
Epoch 161/1000
17 - val_loss: 0.5057 - val_accuracy: 0.8033
Epoch 162/1000
46 - val_loss: 0.5105 - val_accuracy: 0.7869
Epoch 163/1000
76 - val_loss: 0.5006 - val_accuracy: 0.7869
Epoch 164/1000
87 - val_loss: 0.5192 - val_accuracy: 0.7869
Epoch 165/1000
46 - val_loss: 0.4964 - val_accuracy: 0.7869
Epoch 166/1000
87 - val_loss: 0.5011 - val_accuracy: 0.8033
Epoch 167/1000
28 - val_loss: 0.4932 - val_accuracy: 0.8033
Epoch 168/1000
99 - val_loss: 0.4916 - val_accuracy: 0.7869
```

```
Epoch 169/1000
28 - val loss: 0.4928 - val accuracy: 0.8033
Epoch 170/1000
28 - val_loss: 0.4873 - val_accuracy: 0.8033
Epoch 171/1000
17 - val_loss: 0.5459 - val_accuracy: 0.7377
Epoch 172/1000
76 - val_loss: 0.4941 - val_accuracy: 0.7213
Epoch 173/1000
28 - val_loss: 0.5021 - val_accuracy: 0.8033
Epoch 174/1000
87 - val_loss: 0.4833 - val_accuracy: 0.7705
Epoch 175/1000
17 - val_loss: 0.4871 - val_accuracy: 0.8361
Epoch 176/1000
10 - val_loss: 0.4769 - val_accuracy: 0.8033
Epoch 177/1000
28 - val_loss: 0.4826 - val_accuracy: 0.8361
Epoch 178/1000
58 - val_loss: 0.4754 - val_accuracy: 0.7869
Epoch 179/1000
76 - val_loss: 0.5030 - val_accuracy: 0.7705
Epoch 180/1000
17 - val_loss: 0.4718 - val_accuracy: 0.8033
Epoch 181/1000
58 - val_loss: 0.4711 - val_accuracy: 0.8361
Epoch 182/1000
28 - val_loss: 0.4675 - val_accuracy: 0.8197
Epoch 183/1000
87 - val_loss: 0.4674 - val_accuracy: 0.8361
Epoch 184/1000
15/15 [==============] - 0s 6ms/step - loss: 0.4238 - accuracy: 0.81
69 - val_loss: 0.4653 - val_accuracy: 0.8197
Epoch 185/1000
39 - val_loss: 0.4791 - val_accuracy: 0.7869
Epoch 186/1000
87 - val_loss: 0.4673 - val_accuracy: 0.7541
Epoch 187/1000
```

```
69 - val_loss: 0.4620 - val_accuracy: 0.8525
Epoch 188/1000
39 - val_loss: 0.4563 - val_accuracy: 0.8197
Epoch 189/1000
87 - val loss: 0.4824 - val accuracy: 0.7705
Epoch 190/1000
39 - val_loss: 0.4586 - val_accuracy: 0.8525
Epoch 191/1000
28 - val_loss: 0.4570 - val_accuracy: 0.8525
Epoch 192/1000
28 - val_loss: 0.4496 - val_accuracy: 0.8525
Epoch 193/1000
39 - val loss: 0.4490 - val accuracy: 0.8689
Epoch 194/1000
69 - val_loss: 0.4514 - val_accuracy: 0.8525
Epoch 195/1000
28 - val_loss: 0.4446 - val_accuracy: 0.8852
Epoch 196/1000
51 - val_loss: 0.4415 - val_accuracy: 0.8852
Epoch 197/1000
80 - val_loss: 0.4406 - val_accuracy: 0.8361
Epoch 198/1000
58 - val_loss: 0.4904 - val_accuracy: 0.7705
Epoch 199/1000
76 - val_loss: 0.4487 - val_accuracy: 0.7377
Epoch 200/1000
46 - val_loss: 0.4681 - val_accuracy: 0.7869
Epoch 201/1000
58 - val_loss: 0.4409 - val_accuracy: 0.7869
Epoch 202/1000
80 - val_loss: 0.4444 - val_accuracy: 0.8361
Epoch 203/1000
80 - val_loss: 0.4382 - val_accuracy: 0.8689
Epoch 204/1000
80 - val_loss: 0.4307 - val_accuracy: 0.8361
Epoch 205/1000
39 - val_loss: 0.4362 - val_accuracy: 0.8525
Epoch 206/1000
```

```
51 - val_loss: 0.4276 - val_accuracy: 0.8852
Epoch 207/1000
15/15 [=============] - 0s 6ms/step - loss: 0.3982 - accuracy: 0.83
10 - val_loss: 0.4323 - val_accuracy: 0.8525
Epoch 208/1000
10 - val_loss: 0.4247 - val_accuracy: 0.8689
Epoch 209/1000
10 - val_loss: 0.4251 - val_accuracy: 0.8525
Epoch 210/1000
69 - val_loss: 0.4540 - val_accuracy: 0.8033
Epoch 211/1000
69 - val_loss: 0.4257 - val_accuracy: 0.8689
Epoch 212/1000
80 - val_loss: 0.4298 - val_accuracy: 0.8525
Epoch 213/1000
10 - val_loss: 0.4206 - val_accuracy: 0.8525
Epoch 214/1000
99 - val_loss: 0.4548 - val_accuracy: 0.8197
Epoch 215/1000
28 - val_loss: 0.4257 - val_accuracy: 0.7705
Epoch 216/1000
80 - val_loss: 0.4319 - val_accuracy: 0.8525
Epoch 217/1000
51 - val_loss: 0.4156 - val_accuracy: 0.8689
Epoch 218/1000
80 - val_loss: 0.4199 - val_accuracy: 0.8525
Epoch 219/1000
39 - val loss: 0.4120 - val accuracy: 0.8525
Epoch 220/1000
39 - val_loss: 0.4096 - val_accuracy: 0.8525
Epoch 221/1000
10 - val_loss: 0.4155 - val_accuracy: 0.8525
Epoch 222/1000
80 - val_loss: 0.4165 - val_accuracy: 0.8525
Epoch 223/1000
10 - val_loss: 0.4095 - val_accuracy: 0.8525
Epoch 224/1000
28 - val_loss: 0.4303 - val_accuracy: 0.8525
```

```
Epoch 225/1000
21 - val loss: 0.4074 - val accuracy: 0.8525
Epoch 226/1000
10 - val_loss: 0.4072 - val_accuracy: 0.8525
Epoch 227/1000
21 - val_loss: 0.4064 - val_accuracy: 0.7869
Epoch 228/1000
21 - val_loss: 0.4039 - val_accuracy: 0.8525
Epoch 229/1000
10 - val_loss: 0.4033 - val_accuracy: 0.8525
Epoch 230/1000
92 - val_loss: 0.4278 - val_accuracy: 0.8525
Epoch 231/1000
15/15 [============] - 0s 6ms/step - loss: 0.4208 - accuracy: 0.82
39 - val_loss: 0.4082 - val_accuracy: 0.8197
Epoch 232/1000
10 - val_loss: 0.4038 - val_accuracy: 0.8525
Epoch 233/1000
51 - val_loss: 0.4000 - val_accuracy: 0.8525
Epoch 234/1000
10 - val_loss: 0.4058 - val_accuracy: 0.8033
Epoch 235/1000
51 - val_loss: 0.3981 - val_accuracy: 0.8525
Epoch 236/1000
10 - val_loss: 0.4021 - val_accuracy: 0.8033
Epoch 237/1000
51 - val_loss: 0.4124 - val_accuracy: 0.8689
Epoch 238/1000
10 - val_loss: 0.4046 - val_accuracy: 0.8033
Epoch 239/1000
80 - val_loss: 0.4240 - val_accuracy: 0.8525
Epoch 240/1000
10 - val_loss: 0.4075 - val_accuracy: 0.8033
Epoch 241/1000
80 - val_loss: 0.4006 - val_accuracy: 0.8033
Epoch 242/1000
92 - val_loss: 0.3960 - val_accuracy: 0.8197
Epoch 243/1000
```

```
51 - val_loss: 0.3966 - val_accuracy: 0.8689
Epoch 244/1000
51 - val_loss: 0.3936 - val_accuracy: 0.8361
Epoch 245/1000
92 - val loss: 0.3954 - val accuracy: 0.8689
Epoch 246/1000
51 - val_loss: 0.4023 - val_accuracy: 0.8689
Epoch 247/1000
51 - val_loss: 0.3934 - val_accuracy: 0.8361
Epoch 248/1000
21 - val_loss: 0.4004 - val_accuracy: 0.8689
Epoch 249/1000
51 - val loss: 0.3920 - val accuracy: 0.8525
Epoch 250/1000
21 - val_loss: 0.3915 - val_accuracy: 0.8689
Epoch 251/1000
21 - val_loss: 0.3856 - val_accuracy: 0.8525
Epoch 252/1000
80 - val_loss: 0.3875 - val_accuracy: 0.8361
Epoch 253/1000
51 - val_loss: 0.4091 - val_accuracy: 0.8689
Epoch 254/1000
51 - val_loss: 0.3848 - val_accuracy: 0.8361
Epoch 255/1000
62 - val_loss: 0.3827 - val_accuracy: 0.8361
Epoch 256/1000
51 - val_loss: 0.4037 - val_accuracy: 0.8689
Epoch 257/1000
21 - val_loss: 0.3909 - val_accuracy: 0.8852
Epoch 258/1000
69 - val_loss: 0.3866 - val_accuracy: 0.8361
Epoch 259/1000
92 - val_loss: 0.3854 - val_accuracy: 0.8525
Epoch 260/1000
21 - val_loss: 0.4030 - val_accuracy: 0.8689
Epoch 261/1000
10 - val_loss: 0.3976 - val_accuracy: 0.7869
Epoch 262/1000
```

```
51 - val_loss: 0.3884 - val_accuracy: 0.8852
   Epoch 263/1000
   15/15 [=============] - 0s 6ms/step - loss: 0.3986 - accuracy: 0.84
   51 - val_loss: 0.4005 - val_accuracy: 0.8689
   Epoch 264/1000
   39 - val_loss: 0.3866 - val_accuracy: 0.8361
   Epoch 265/1000
   92 - val_loss: 0.3855 - val_accuracy: 0.8689
   Epoch 266/1000
   92 - val_loss: 0.3862 - val_accuracy: 0.8525
   Epoch 267/1000
   21 - val_loss: 0.3870 - val_accuracy: 0.8852
   Epoch 268/1000
   92 - val_loss: 0.3841 - val_accuracy: 0.8525
   Epoch 269/1000
   15/15 [=============] - 0s 6ms/step - loss: 0.3777 - accuracy: 0.87
   32 - val_loss: 0.4099 - val_accuracy: 0.8525
   Epoch 270/1000
   69 - val_loss: 0.3960 - val_accuracy: 0.7869
   Epoch 271/1000
   51 - val_loss: 0.3943 - val_accuracy: 0.8852
   Epoch 272/1000
   21 - val_loss: 0.3886 - val_accuracy: 0.8852
   Epoch 273/1000
   69 - val_loss: 0.4359 - val_accuracy: 0.7377
   Epoch 274/1000
   39 - val_loss: 0.4184 - val_accuracy: 0.8525
   Epoch 275/1000
   80 - val loss: 0.3888 - val accuracy: 0.8033
   Epoch 275: early stopping
In [ ]: # Make predictions with model on test set
    y_pred = classifier.predict(X_test)
    y_pred = (y_pred > 0.5) # If greater than .5 then model returns True or present for
   4/4 [======= ] - 0s 2ms/step
   4/4 [======= ] - 0s 2ms/step
In [ ]: # Calculate the Accuracy
    from sklearn.metrics import accuracy score
     score=accuracy_score(y_pred,y_test)
     print("TensorFLow Accuracy:",score*100,"%")
```

15/15 [=============] - 0s 6ms/step - loss: 0.3772 - accuracy: 0.84

```
TensorFlowPred1 = classifier.predict(XTestValues1)
        TensorFlowPred2 = classifier.predict(XTestValues2)
      TensorFLow Accuracy: 83.0 %
      1/1 [=======] - 0s 28ms/step
      1/1 [=======] - 0s 28ms/step
      1/1 [=======] - 0s 30ms/step
In [ ]: # Make predictions with example test values
        print(TensorFlowPred1)
        print(TensorFlowPred2)
      [[0.18484353]]
      [[0.9896394]]
In [ ]: from sklearn.model_selection import RepeatedKFold
        from sklearn.linear_model import LinearRegression
        from sklearn.linear_model import Ridge
        # Define K-Fold Cross Validation
        #cv = RepeatedKFold(n_splits=203,n_repeats=3,random_state=1)
        # Define predictor and target variables
        X = df[["age",'sex','cp','trestbps','chol','fbs','restecg','thalach','exang','oldpe
        y = df["target"]
        # Linear Regression
        LinearModel1 = LinearRegression().fit(X_train, y_train)
        LinearModel1.predict(X_test)
        accuracy = LinearModel1.score(X_test,y_test)
        print('The predicted accuracy for Linear Regression is: {0:0.4f}'.format((accuracy*
        # Ridge Model
        RidgeModel1 = Ridge(alpha=10)
        RidgeModel1.fit(X_train,y_train)
        accuracy = RidgeModel1.score(X_test,y_test)
        print('The Predicted accuracy for the Ridge Model is: {0:0.4f}'.format((accuracy*10
      The predicted accuracy for Linear Regression is: 44.6637 %
      The Predicted accuracy for the Ridge Model is: 45.1017 %
```