Importing the required libraries needed for the development of the model

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import load_model
from sklearn.metrics import confusion_matrix, classification_report
```

Loading the dataset

```
h = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/Heart Disease data.csv")
```

Info of the dataset

```
h.info()
```

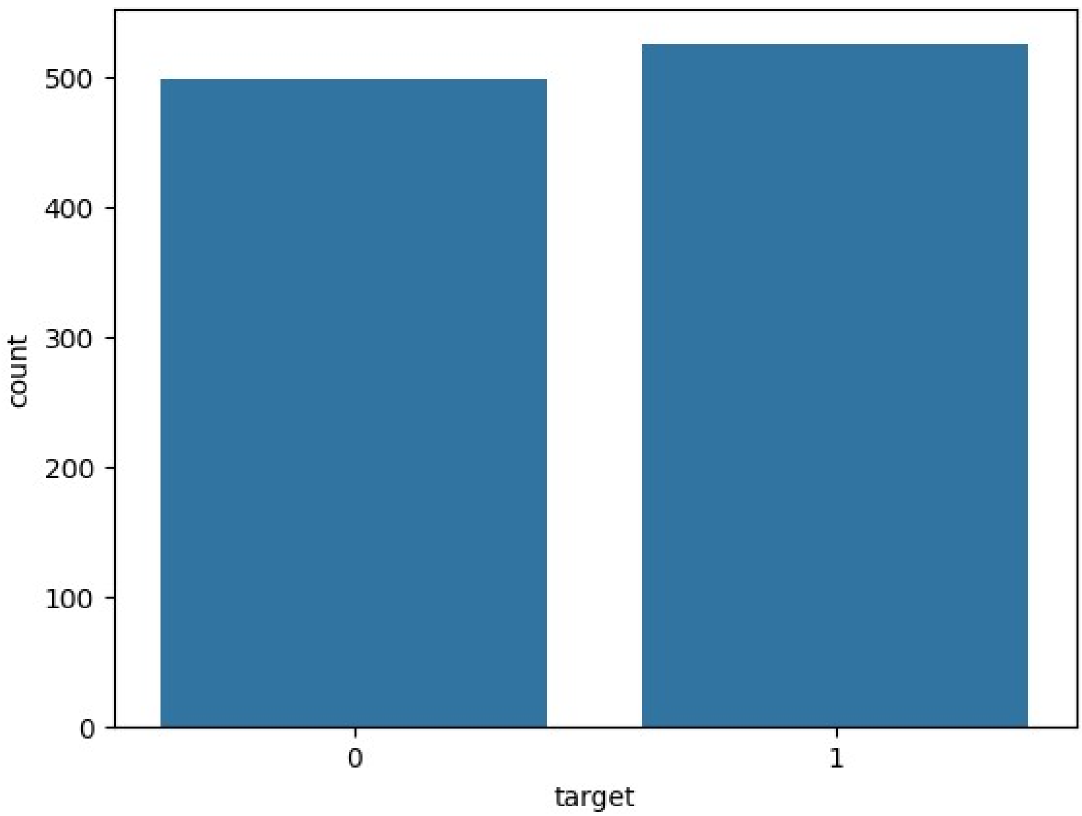
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1025 non-null   int64
 1   sex       1025 non-null   int64
 2   cp        1025 non-null   int64
 3   trestbps  1025 non-null   int64
 4   chol      1025 non-null   int64
 5   fbs       1025 non-null   int64
 6   restecg   1025 non-null   int64
 7   thalach   1025 non-null   int64
 8   exang     1025 non-null   int64
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64
 11  ca        1025 non-null   int64
 12  thal      1025 non-null   int64
```

```
 13  target    1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

Countplot of the target

```
sns.countplot(x = "target", data = h)
print("1: Heart Disease present")
print("0: Heart Disease absent")
```

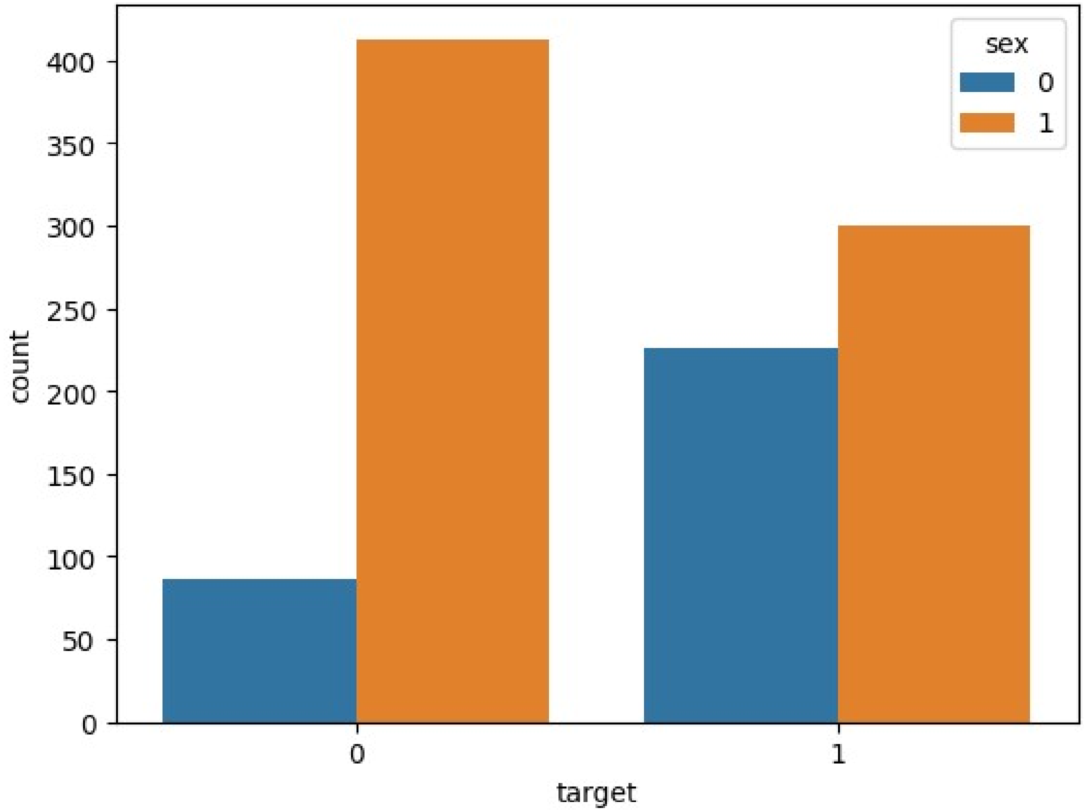
```
1: Heart Disease present
0: Heart Disease absent
```



Countplot of the target with respect to gender

```
sns.countplot(x = "target", data = h, hue = 'sex')
print("sex:\n 1:Male \n 0:Female")
print("target:\n 1: Heart Disease present \n 0: Heart Disease absent
")
```

```
sex:
 1:Male
 0:Female
target:
 1: Heart Disease present
 0: Heart Disease absent
```



Total count of target values

```
h['target'].value_counts()
```

```
target
1    526
0    499
Name: count, dtype: int64
```

Total count of gender

```
h['sex'].value_counts()
```

```
sex
1    713
0    312
Name: count, dtype: int64
```

heatmap of correlation betweem the variables

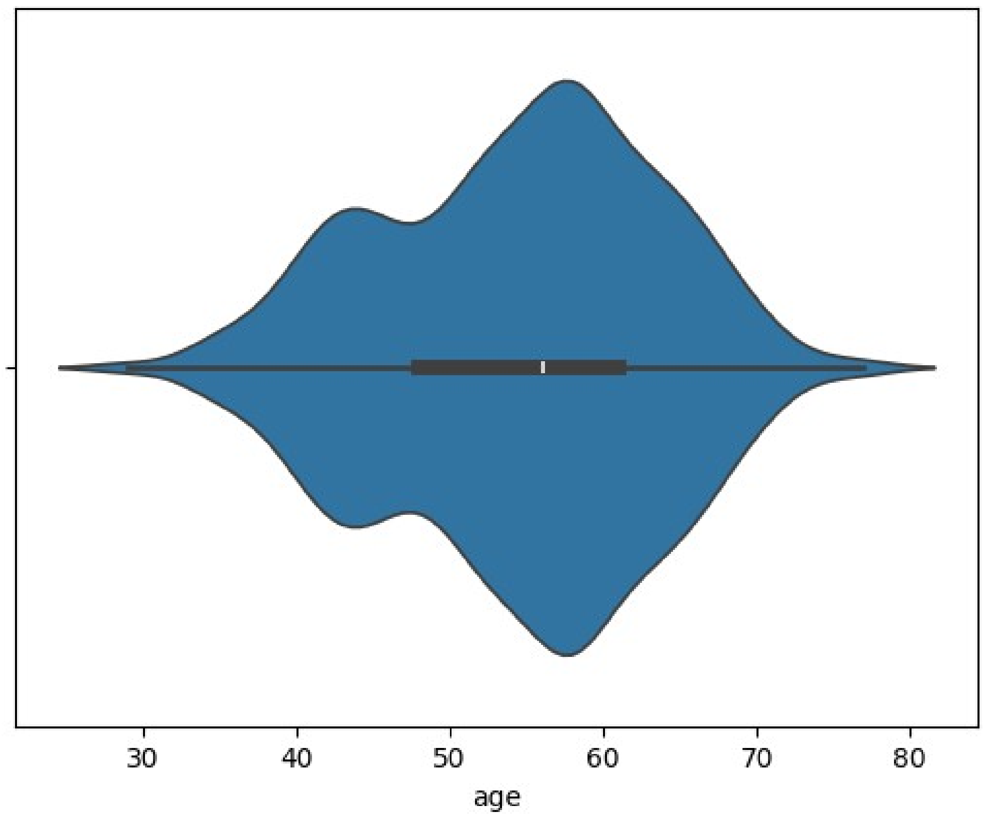
```python
plt.figure(figsize = (12,5))
sns.heatmap(h.corr(), annot = True)
```

```
<Axes: >
```

Vioplot of age

```python
sns.violinplot(x = 'age', data = h)
```

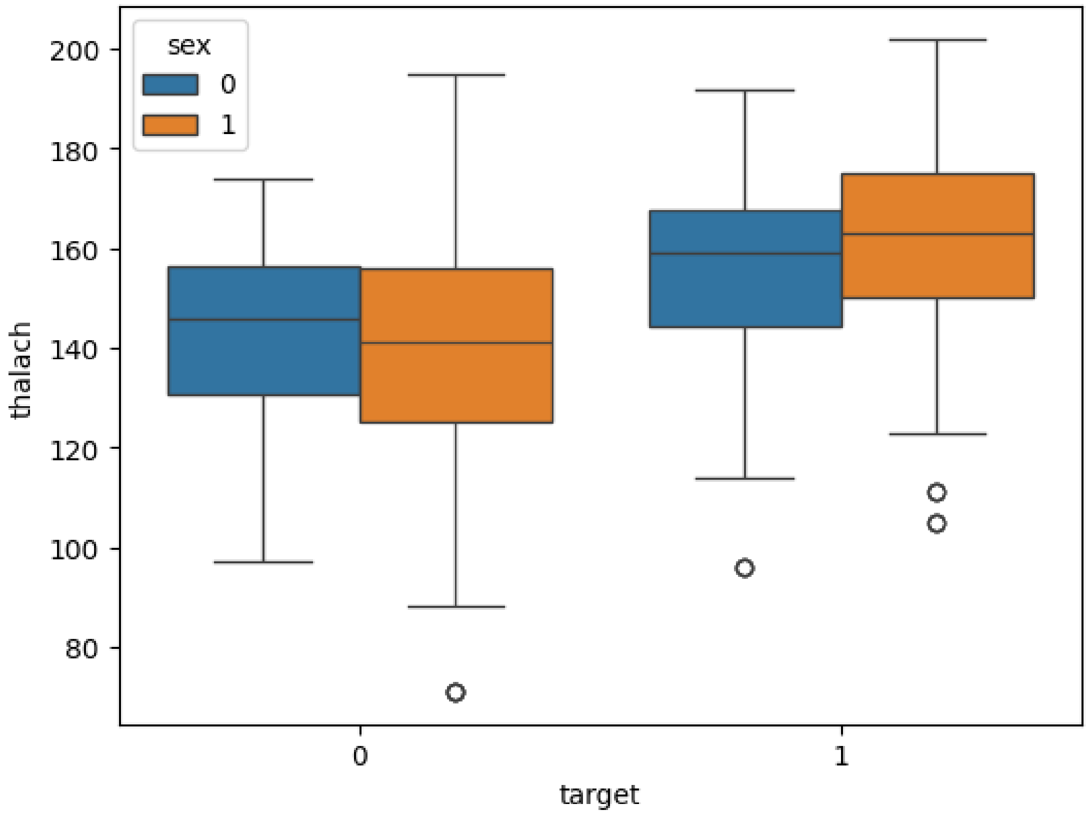
```
<Axes: xlabel='age'>
```



Boxplot of Target

```
sns.boxplot(x = 'target', y = 'thalach', data = h, hue = 'sex')
```

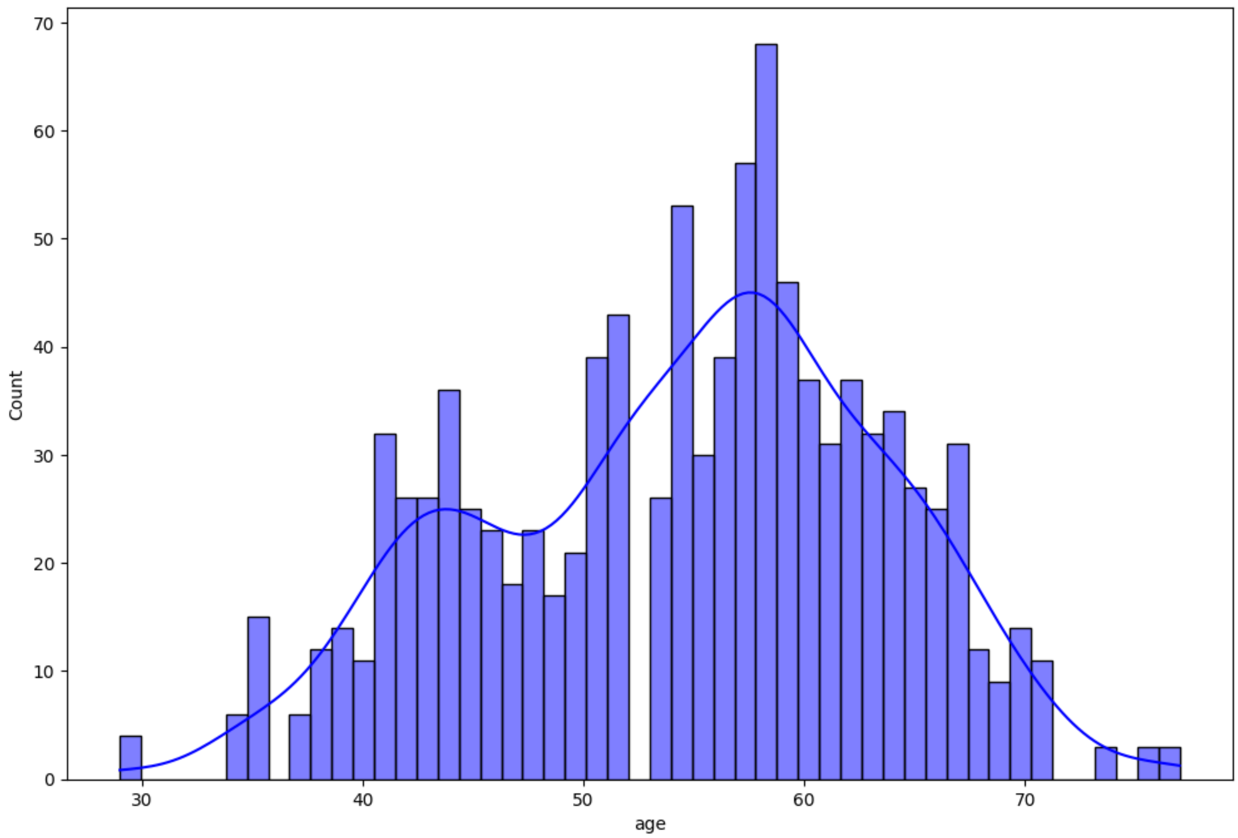
```
<Axes: xlabel='target', ylabel='thalach'>
```



Histplot of age

```
plt.figure(figsize = (12,8))
sns.histplot(h['age'], color = 'b',kde = True, bins = 50)
```

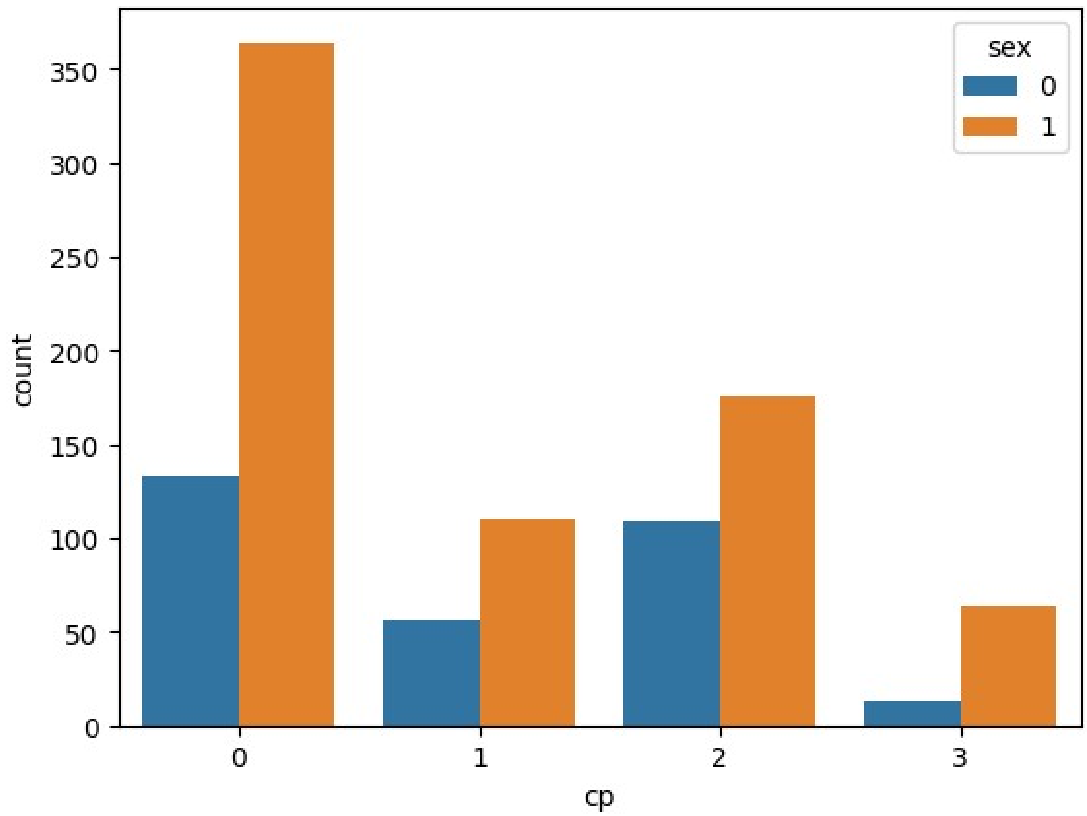
```
<Axes: xlabel='age', ylabel='Count'>
```



Countplot of cp with respect to gender

```
sns.countplot(x = 'cp', data = h, hue = 'sex')
```

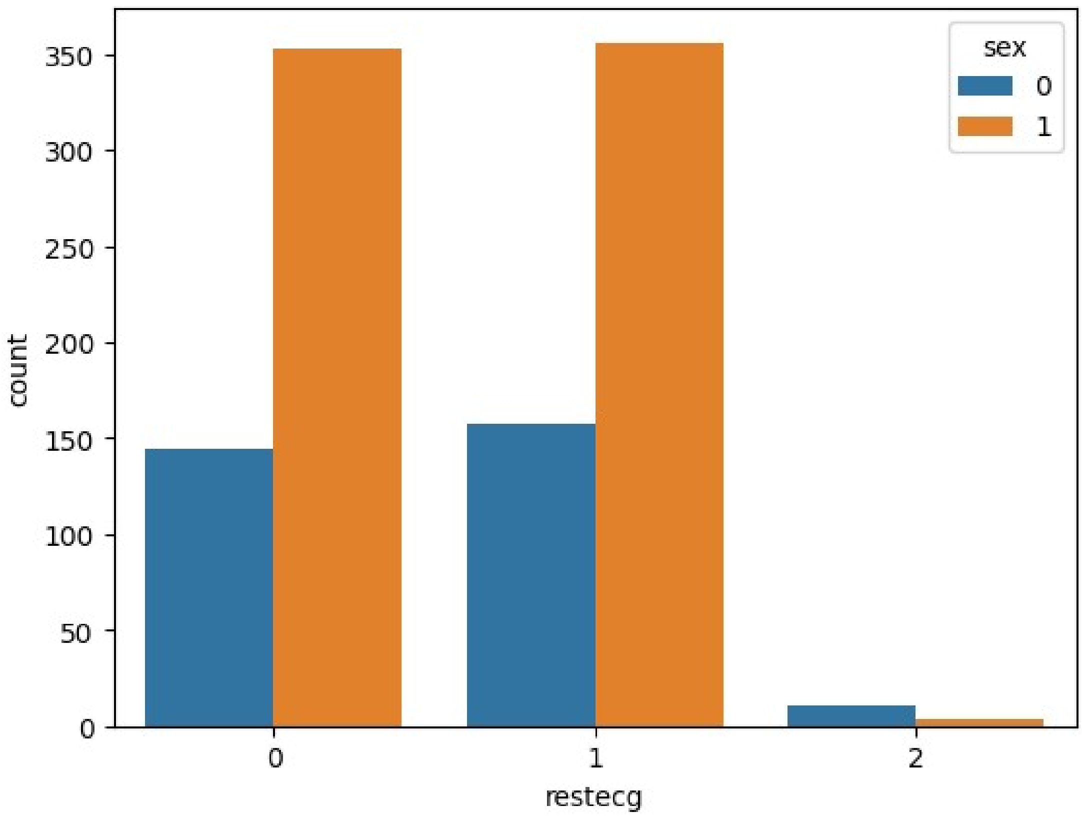
```
<Axes: xlabel='cp', ylabel='count'>
```



Countplot of rest ecg with respect to gender

```
sns.countplot(x = 'restecg', data = h, hue = 'sex')
```

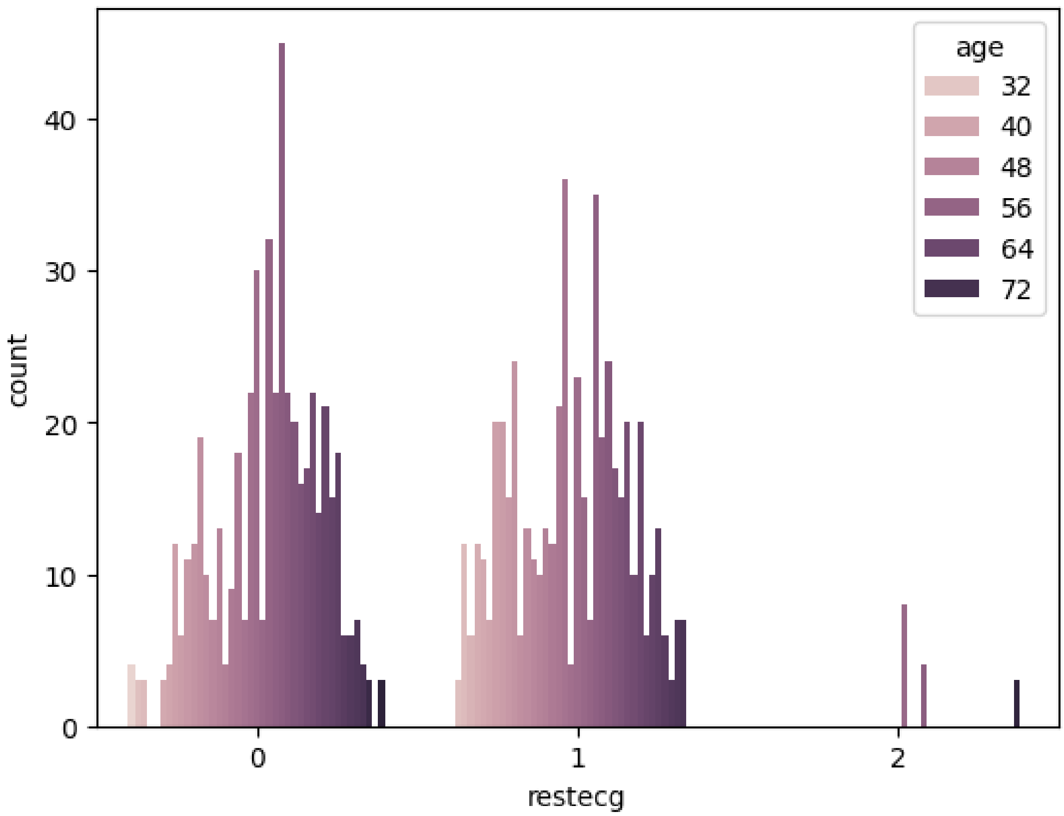
```
<Axes: xlabel='restecg', ylabel='count'>
```



Displaying the rest ecg variable with respect to age

```
sns.countplot(x = 'restecg', data = h, hue = 'age')
```

```
<Axes: xlabel='restecg', ylabel='count'>
```



Selecting the target and predictor variable

```
X = h.drop('target', axis = 1)
y = h[['target']]
```

Scaled values

```
Scaler = MinMaxScaler()
X_scaled = Scaler.fit_transform(X)
y_scaled = Scaler.fit_transform(y)

X_scaled.shape

(1025, 13)

y_scaled.shape

(1025, 1)
```

Printing the scaled values

```
print("X_scaled values:\n", X_scaled)
print("y_scaled values:\n", y_scaled)
```

```
X_scaled values:
 [[0.47916667 1.         0.         ... 1.         0.5        1.
]
 [0.5        1.         0.         ... 0.         0.         1.
]
 [0.85416667 1.         0.         ... 0.         0.         1.
]
 ...
 [0.375      1.         0.         ... 0.5        0.25
0.66666667]
 [0.4375     0.         0.         ... 1.         0.
0.66666667]
 [0.52083333 1.         0.         ... 0.5        0.25       1.
]]
y_scaled values:
 [[0.]
 [0.]
 [0.]
 ...
 [0.]
 [1.]
 [0.]]
```

Splitting the dataset into training and testing

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled,
y_scaled, test_size = 0.2)
```

Printing the shapes of the sets

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(820, 13)
(820, 1)
(205, 13)
(205, 1)
```

Developing the model

```
Classifier_model = tf.keras.models.Sequential([Dense(64, activation = 'relu', input_shape = (13,)),
                                                Dense(32, activation = 'relu'),
                                                Dense(32, activation = 'relu'),
                                                Dense(16, activation = 'relu'),
                                                Dense(16, activation = 'relu'),
                                                Dense(8, activation = 'relu'),
                                                Dense(1, activation = 'sigmoid')])
Classifier_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                896

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 32)                1056

 dense_3 (Dense)             (None, 16)                528

 dense_4 (Dense)             (None, 16)                272

 dense_5 (Dense)             (None, 8)                 136

 dense_6 (Dense)             (None, 1)                 9

=================================================================
Total params: 4977 (19.44 KB)
Trainable params: 4977 (19.44 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Compiling the model

```
Classifier_model.compile(optimizer = 'Adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
es = EarlyStopping(monitor = 'val_loss', patience = 2)
```

```
Classifier_model.fit(X_train, y_train, validation_data = (X_test,
y_test), epochs = 25, callbacks = [es])
```

```
Epoch 1/25
26/26 [==============================] - 16s 66ms/step - loss: 0.6674
- accuracy: 0.5976 - val_loss: 0.6221 - val_accuracy: 0.7122
Epoch 2/25
26/26 [==============================] - 0s 14ms/step - loss: 0.5487 -
accuracy: 0.8049 - val_loss: 0.4860 - val_accuracy: 0.7951
Epoch 3/25
26/26 [==============================] - 0s 10ms/step - loss: 0.4078 -
accuracy: 0.8378 - val_loss: 0.4019 - val_accuracy: 0.8049
Epoch 4/25
26/26 [==============================] - 0s 10ms/step - loss: 0.3677 -
accuracy: 0.8524 - val_loss: 0.3849 - val_accuracy: 0.8341
Epoch 5/25
26/26 [==============================] - 0s 10ms/step - loss: 0.3374 -
accuracy: 0.8646 - val_loss: 0.3607 - val_accuracy: 0.8537
Epoch 6/25
26/26 [==============================] - 0s 13ms/step - loss: 0.3390 -
accuracy: 0.8683 - val_loss: 0.3643 - val_accuracy: 0.8780
Epoch 7/25
26/26 [==============================] - 1s 21ms/step - loss: 0.3193 -
accuracy: 0.8671 - val_loss: 0.3390 - val_accuracy: 0.8683
Epoch 8/25
26/26 [==============================] - 0s 14ms/step - loss: 0.2979 -
accuracy: 0.8829 - val_loss: 0.3255 - val_accuracy: 0.8829
Epoch 9/25
26/26 [==============================] - 0s 16ms/step - loss: 0.2891 -
accuracy: 0.8902 - val_loss: 0.3124 - val_accuracy: 0.8878
Epoch 10/25
26/26 [==============================] - 0s 11ms/step - loss: 0.2804 -
accuracy: 0.8988 - val_loss: 0.3296 - val_accuracy: 0.8488
Epoch 11/25
26/26 [==============================] - 0s 19ms/step - loss: 0.2824 -
accuracy: 0.8841 - val_loss: 0.2954 - val_accuracy: 0.8780
Epoch 12/25
26/26 [==============================] - 0s 19ms/step - loss: 0.2686 -
accuracy: 0.8988 - val_loss: 0.2803 - val_accuracy: 0.8976
Epoch 13/25
26/26 [==============================] - 0s 12ms/step - loss: 0.2525 -
accuracy: 0.9049 - val_loss: 0.2800 - val_accuracy: 0.8878
Epoch 14/25
26/26 [==============================] - 0s 9ms/step - loss: 0.2493 -
accuracy: 0.9073 - val_loss: 0.2627 - val_accuracy: 0.9073
Epoch 15/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2452 -
accuracy: 0.9024 - val_loss: 0.2636 - val_accuracy: 0.8927
Epoch 16/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2337 -
```

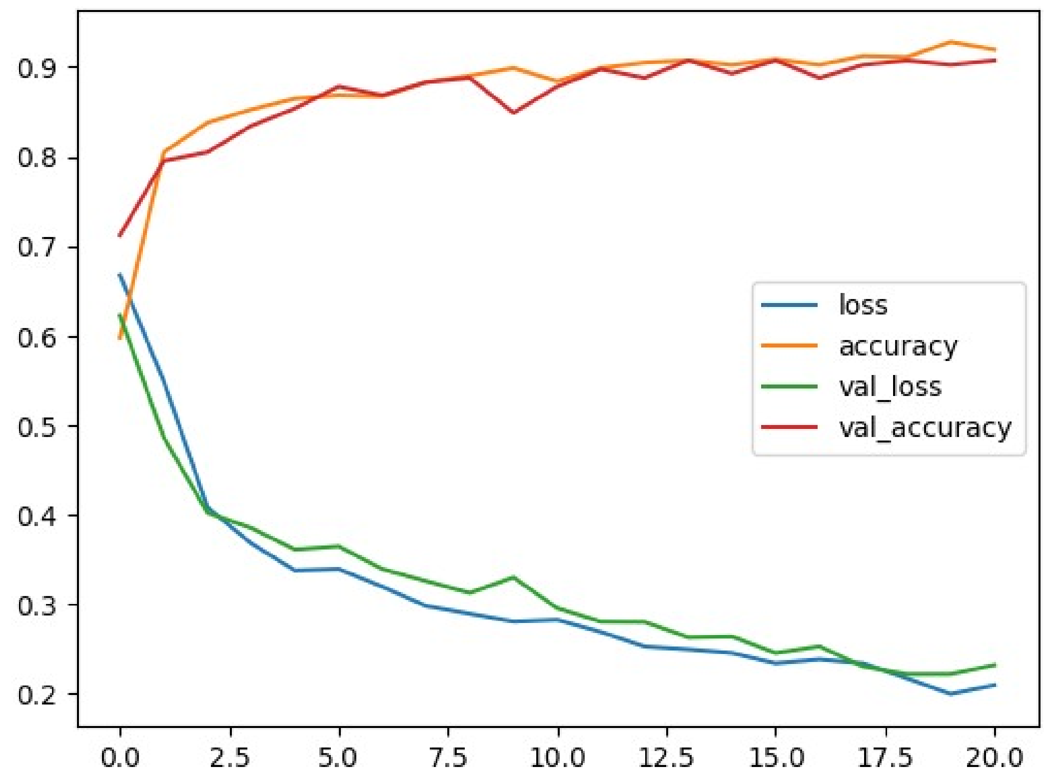
```
accuracy: 0.9085 - val_loss: 0.2451 - val_accuracy: 0.9073
Epoch 17/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2382 -
accuracy: 0.9024 - val_loss: 0.2526 - val_accuracy: 0.8878
Epoch 18/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2337 -
accuracy: 0.9122 - val_loss: 0.2301 - val_accuracy: 0.9024
Epoch 19/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2169 -
accuracy: 0.9110 - val_loss: 0.2215 - val_accuracy: 0.9073
Epoch 20/25
26/26 [==============================] - 0s 7ms/step - loss: 0.1995 -
accuracy: 0.9280 - val_loss: 0.2216 - val_accuracy: 0.9024
Epoch 21/25
26/26 [==============================] - 0s 7ms/step - loss: 0.2093 -
accuracy: 0.9195 - val_loss: 0.2317 - val_accuracy: 0.9073

<keras.src.callbacks.History at 0x7d60ef74a6b0>
```

Plotting the history of the model

```
hist = Classifier_model.history.history
new_hist = pd.DataFrame(hist)
new_hist.plot()

<Axes: >
```



Calculating the predictions

```
y_test_predict = Classifier_model.predict(X_test)
y_train_predict = Classifier_model.predict(X_train)
```

```
7/7 [==============================] - 0s 2ms/step
26/26 [==============================] - 0s 2ms/step
```

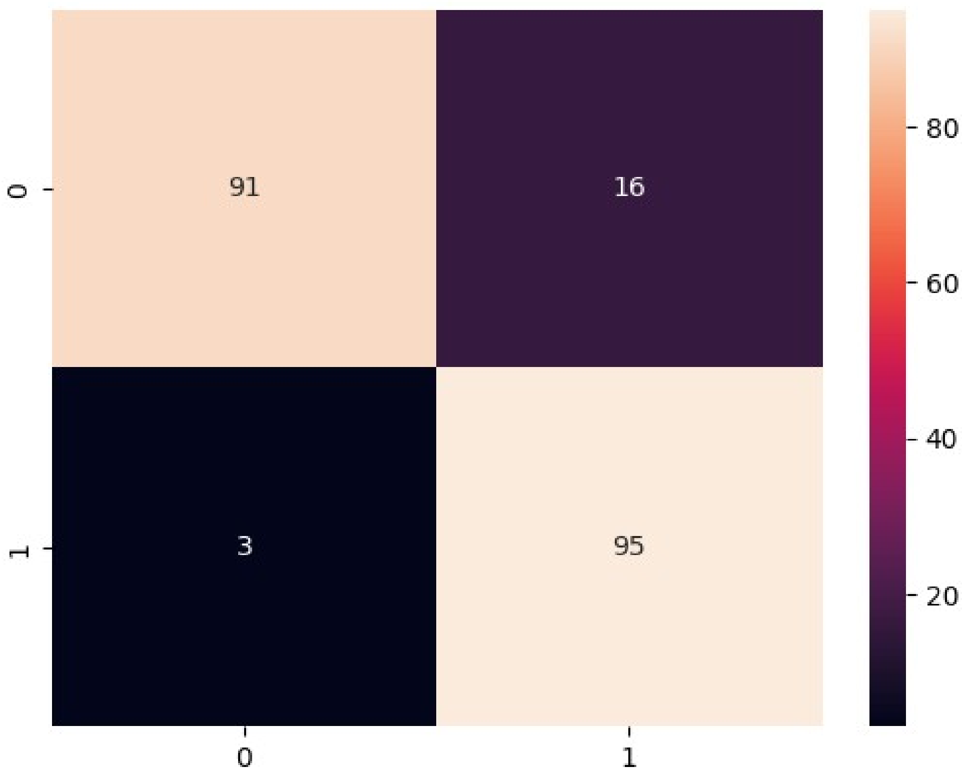
```
y_test_predict = y_test_predict > 0.5
y_train_predict = y_train_predict > 0.5
```

```
cm = confusion_matrix(y_test_predict, y_test)
cm2 = confusion_matrix(y_train_predict, y_train)
```

Confusion matrix of testing set

```
sns.heatmap(cm, annot = True)
```

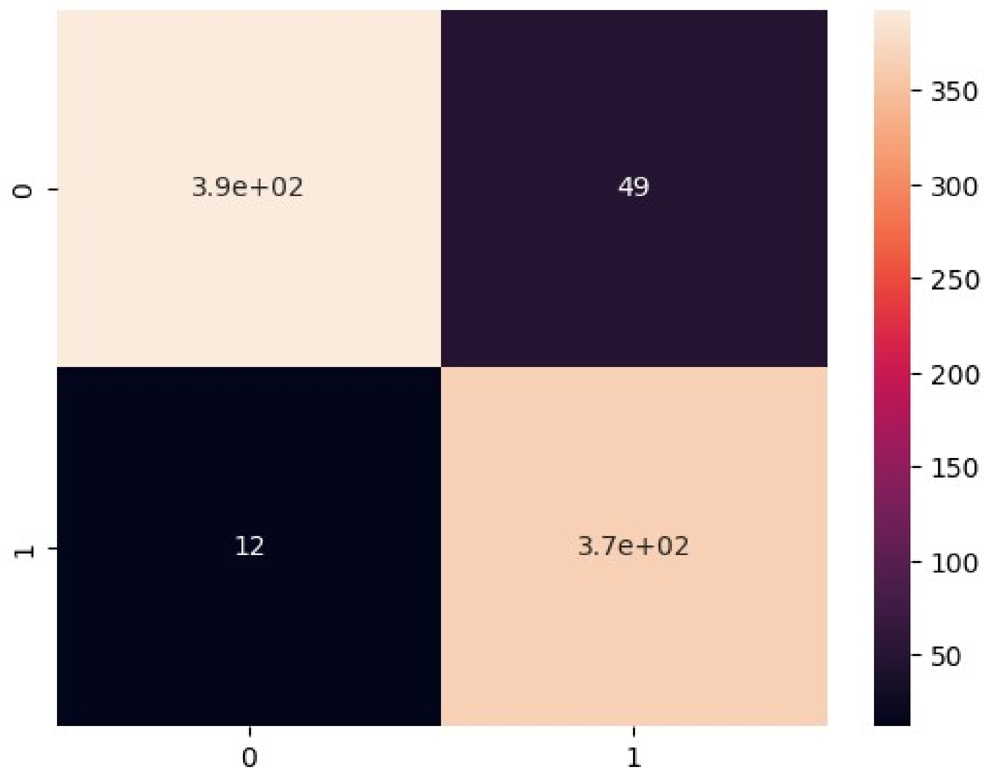
```
<Axes: >
```



Confusion matrix of training set

```
sns.heatmap(cm2, annot = True)
```

```
<Axes: >
```



Classification report of the model

```
print("Training Report:\n", classification_report(y_test_predict,
y_test))
print("Testing Report:\n", classification_report(y_train_predict,
y_train))
```

```
Training Report:
               precision    recall  f1-score   support

       False       0.97      0.85      0.91       107
        True       0.86      0.97      0.91        98

    accuracy                           0.91       205
   macro avg       0.91      0.91      0.91       205
weighted avg       0.91      0.91      0.91       205

Testing Report:
               precision    recall  f1-score   support

       False       0.97      0.89      0.93       442
        True       0.88      0.97      0.92       378

    accuracy                           0.93       820
   macro avg       0.93      0.93      0.93       820
```

```
weighted avg       0.93      0.93      0.93       820
```

Saving the model

```python
Classifier_model.save("Heart_Disease_Predictor.h5")
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/
training.py:3103: UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
  saving_api.save_model(
```

Storing the scaler

```python
import pickle
pickle.dump(Scaler,open("scaler.pkl", "wb"))

model = load_model("Heart_Disease_Predictor.h5")
```

Deployment function for the model

```python
def return_prediction(model, Scaler, sample_json):
  a = sample_json['age']
  s = sample_json['sex']
  c = sample_json['trestbps']
  o = sample_json['chol']
  f = sample_json['fbs']
  r = sample_json['restecg']
  t = sample_json['thalach']
  e = sample_json['exang']
  p = sample_json['oldpeak']
  st = sample_json['slope']
  cc = sample_json['ca']
  l = sample_json['thal']
  dc = [[a,s,c,o,f,r,t,e,p,st,cc,l]]
  dc = Scaler.fit_transform(dc)
  predict = model.predict(dc)
  classes = np.argmax(predict, axis = 1)
  return classes
```