## **MACHINE LEARNING**

**Course-End Project: Healthcare** 

## **PROBLEM STATEMENT:**

To develop the model and predict the heart attacks that are causing the deaths globally using the given relevant dataset variables

## **TASK-1**:

Perform preliminary data inspection and report the findings on the structure of the
data, missing values, duplicates, etc.
Based on these findings, remove duplicates (if any) and treat missing values
using an appropriate strategy

## CODE:

heathcare\_df = pd.read\_excel("Healthcare\_cep1\_dataset.xlsx")
heathcare\_df.head()
heathcare\_df.tail()
heathcare\_df.shape

## Screenshot:

in [7]: #Displays the top 5 rows of the dataset
heathcare\_df.head()

ot [7]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	8.0	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

in [8]: #Displays the bottom 5 rows of the dataset
heathcare\_df.tail()

ut[8]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

In [9]: # To find the total number of rows and columns
heathcare\_df.shape

lut[9]: (303, 14)

#### Code

heathcare\_df.info()
heathcare\_df.isnull().sum()

#### Screenshot:

```
heathcare_df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 303 entries, 0 to 302
       Data columns (total 14 columns):
             Column
                       Non-Null Count Dtype
                       303 non-null
         0
             age
                                       int64
         1
            sex
                       303 non-null
                                       int64
         2
                       303 non-null
                                       int64
             ср
         3
            trestbps
                       303 non-null
                                       int64
         4
             chol
                       303 non-null
                                       int64
            fbs
                       303 non-null
                                       int64
         6
                       303 non-null
                                       int64
             restecq
         7
            thalach
                       303 non-null
                                       int64
         8
                       303 non-null
                                       int64
             exang
         9
             oldpeak
                       303 non-null
                                       float64
         10 slope
                       303 non-null
                                       int64
                                       int64
         11 ca
                       303 non-null
         12 thal
                       303 non-null
                                       int64
                       303 non-null
                                       int64
        13 target
       dtypes: float64(1), int64(13)
       memory usage: 33.3 KB
[12]: # To find the missing values in each column of the entire dataframe(ALL COLUMNS
       heathcare_df.isnull().sum()
ıt[12]: age
                    0
        sex
       ср
       trestbps
                    0
       chol
                    0
       fbs
                    0
        restecg
                    0
       thalach
```

CONCLUDING FROM ABOVE INFO THAT THE DATASET HAS NO MISSING VALUES

## TASK -2

## ☐ EXPLAINING THE DATA DISTRIBUTION AND THE RELATED FACTORS¶

```
Code:
```

```
heathcare_df["target"].value_counts()

sns.countplot(data = heathcare_df , x ="target", width=0.3)
plt.xlabel("One and zeros of CVDS")
plt.ylabel("Count of ones and zeros")
plt.title('Countplot of CVD')
plt.xticks(rotation=90)
#Adjust the figure size (optional)
plt.figure(figsize=(10, 10))
plt.show()
```

```
In [14]: # Finding the number of positive CVD'S and negative CVD'S
heathcare_df["target"].value_counts()
Out[14]: 1
                     138
             Name: target, dtype: int64
In [40]: # FINDING THE COUNT OF CVD'S USING COUNTPLOT
             sns.countplot(data = heathcare_df , x ="target", width=0.3)
plt.xlabel("One and zeros of CVDS")
plt.ylabel("Count of ones and zeros")
plt.title('Countplot of CVD')
             plt.xticks(rotation=90)
             #Adjust the figure size (optional)
plt.figure(figsize=(10, 10))
             plt.show()
                                                       Countplot of CVD
       click to scroll output; double click to hide
                   140
               Count of ones and zeros
                   120
                   100
                    80
                    60
                    40
                    20
                                                     One and zeros of CVDS
              <Figure size 1000x1000 with 0 Axes>
```

## Code:

heathcare\_df.describe()

print(heathcare\_df.corr()['target'].abs().sort\_values(ascending=False))

## **Screenshot**

In [41]: # Displaying the summary of the statistical analysis of the dataset
heathcare\_df.describe()

Out[41]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	31
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373	
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606	
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	

In [42]: #checking the correlation of the variables with respect to target variable

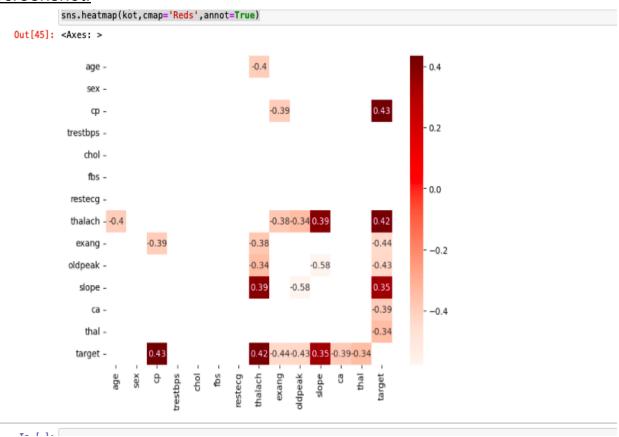
print(heathcare\_df.corr()['target'].abs().sort\_values(ascending=False))

target 1.000000 exang 0.436757 0.433798 oldpeak 0.430696 thalach 0.421741 0.391724 slope 0.345877 thal 0.344029 0.280937 sex age 0.225439 trestbps 0.144931 restecg 0.137230 chol 0.085239 fbs 0.028046

Name: target, dtype: float64

## Code:

```
corr_diagram = heathcare_df.corr()
thresh=0.3
kot=corr_diagram[((corr_diagram>=thresh)|(corr_diagram<=-thresh))&(corr_diagram!=1)]
plt.figure(figsize=(8,6))
sns.heatmap(kot,cmap='Reds',annot=True)</pre>
```



heathcare\_df["sex"].value\_counts()

pd.crosstab(heathcare\_df["target"],heathcare\_df["sex"])

pd.crosstab(heathcare\_df.target,heathcare\_df.sex).plot(kind='bar',figsize=(10,6),color=['yellow','green'])

#### Screenshot:



# Inference from above graph

# 93 males as compared to 72 females are detected with CVD. So males are at a higher risk of CVD

```
pd.crosstab(heathcare df.cp,heathcare df.target)
```

```
heathcare_df['cp'].unique()
```

import warnings

warnings.filterwarnings('ignore')

 $sns.barplot(x=heathcare\_df['cp'],y=heathcare\_df['target'],data=heathcare\_df)$ 

plt.show()



- # Inference from above graph
- # Maximum people(69) who are suffering from non-anginal pain gets detected with CVD.
- # Asymptomatic people(104) are least likely to suffer from heart diseases.

heathcare\_df['restecg'].unique()

sns.barplot(x='restecg',y='target',data=heathcare\_df)
plt.show()

#### Screenshot:

```
In [ ]:
In [69]: # Analysing the restecg feature
heathcare_df['restecg'].unique()
Out[69]: array([0, 1, 2])
In [70]: #RESTECG NOTATIONS ARE TAKEN AS BELOW
             #0- 'resting_ecg'] = 'normal'
#1-'resting_ecg'] = 'abnormal'
#2- 'resting_ecg'] = 'hyper'
In [68]: sns.barplot(x='restecg',y='target',data=heathcare_df)
plt.show()
                  0.7
                  0.6
                  0.5
                  0.4
                  0.3
                  0.2
                  0.1
                  0.0
                                    ò
                                                                1
                                                            restecg
```

#Inference from above graph
#category 1- Abnormal Resting electrocardiographic results show maximum occurences
of a CVD

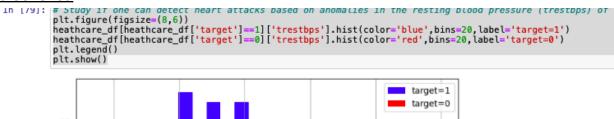
#Study if one can detect heart attacks based on anomalies in the resting blood pressure (trestbps) of a patient

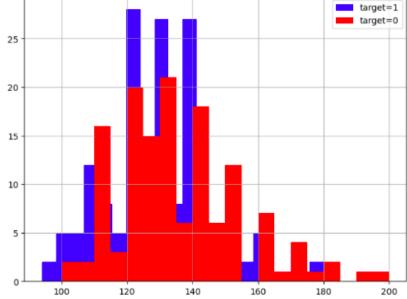
```
plt.figure(figsize=(8,6))
heathcare_df[heathcare_df['target']==1]['trestbps'].hist(color='blue',bins=20,label='target =1')
```

heathcare\_df[heathcare\_df['target']==0]['trestbps'].hist(color='red',bins=20,label='target=0')

plt.legend()
plt.show()

#### Screenshot:





# Inference from above graph

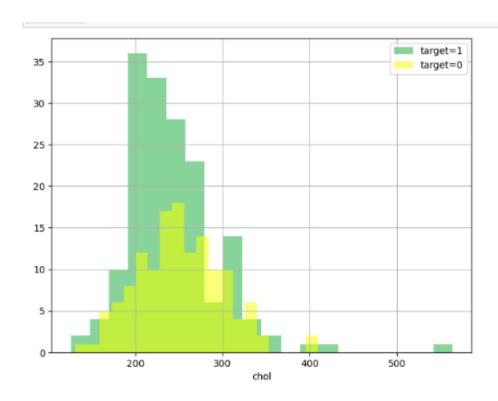
# If trestbps is between 120 to 140 have higher chances of CVD

# Describe the relationship between cholesterol levels and a target variable plt.figure(figsize=(8,6))

heathcare\_df[heathcare\_df['target']==1]['chol'].hist(alpha=0.4,color='green',bins=20,label='target=1')

heathcare\_df[heathcare\_df['target']==0]['chol'].hist(alpha=0.5,color='yellow',bins=20,labe l='target=0')

plt.legend() plt.xlabel('chol') plt.show()

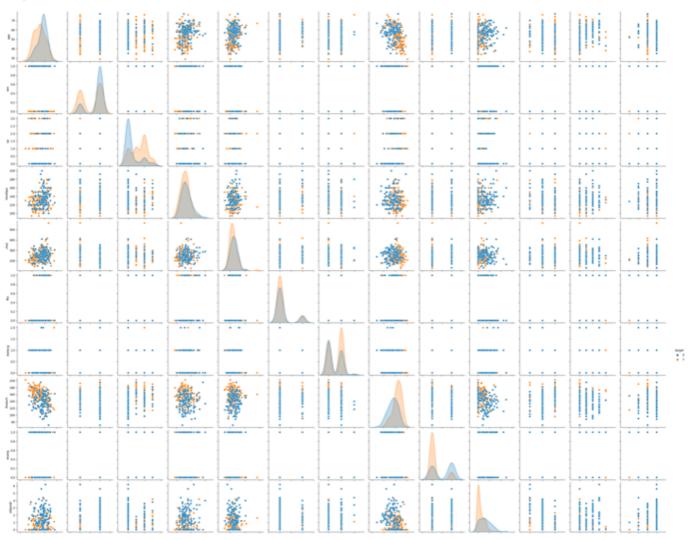


# Use a pair plot to understand the relationship between all the given variables

```
plt.figure(figsize=(8,6))
sns.pairplot(data = heathcare_df,hue='target')
plt.title('CVD')
plt.show()
```

## Screenshot:

<Figure size 800x600 with 0 Axes>



# TASK-3 MODELLING THE DATASET

#### Code:

## **#Splitting the dataset**

from sklearn.model\_selection import train\_test\_split
predictors= heathcare\_df.drop('target',axis=1)
target = heathcare\_df['target']
X\_train,X\_test,y\_train,y\_test=train\_test\_split(predictors,target,test\_size=0.25,random\_st
ate=0)

## #building the logistic regression model

from sklearn.linear\_model import LogisticRegression lr= LogisticRegression() lr.fit(X\_train,y\_train)

y\_pred = Ir.predict(X\_test)

## #Calculating the accuracy

from sklearn.metrics import accuracy\_score score\_lr = round(accuracy\_score(y\_pred,y\_test)\*100,2) print("The accuracy score achieved using logistic regression is: "+ str(score\_lr)+" %")

## #fitting a stats logistic regression model

import statsmodels.api as sm
log\_reg=sm.Logit(y\_train,X\_train).fit()

## #printing the summary reports

print(log reg.summary())

```
In [83]: | from sklearn.model_selection import train_test_split
          predictors= heathcare_df.drop('target',axis=1)
target = heathcare_df['target']
          X_train,X_test,y_train,y_test=train_test_split(predictors,target,test_size=0.25,random_state=0)
In [84]: #building the logistic regression model
from sklearn.linear_model import LogisticRegression
           lr= LogisticRegression()
           lr.fit(X_train,y_train)
Out[84]: v LogisticRegression
           LogisticRegression()
In [85]: y_pred = lr.predict(X_test)
In [86]: from sklearn.metrics import accuracy_score
           score_lr = round(accuracy_score(y_pred,y_test)*100,2)
          print("The accuracy score achieved using logistic regression is: "+ str(score_lr)+" %")
          The accuracy score achieved using logistic regression is: 84.21 %
In [87]: #fitting a stats logistic regression model
import statsmodels.api as sm
          log_reg=sm.Logit(y_train,X_train).fit()
          Optimization terminated successfully.
                    Current function value: 0.343229
                    Iterations 7
In [89]: #printing the summary reports
print(log_reg.summary())
                                        Logit Regression Results
                                                       No. Observations:
Df Residuals:
          Dep. Variable:
                                                                                               227
                                             target
          Model:
                                                                                               214
                                               Logit
                                                       Df Model:
          Method:
                                                MLE
                                                                                                12
                                                                                           0.5028
                                  Wed, 20 Sep 2023
          Date:
                                                       Pseudo R-sau.:
          Time:
                                           14:03:53
                                                       Log-Likelihood:
                                                                                           -77.913
          converged:
                                               True
                                                       LL-Null:
                                                                                           -156.71
          Covariance Type:
                                          nonrobust
                                                       LLR p-value:
                                                                                        1.627e-27
                                      std err
                                                                               [0.025
                                                                                            0.975]
                             coef
                                                                  P>|z|
                           0.0176
                                         0.022
                                                     0.803
                                                                  0.422
                                                                              -0.025
                                                                                             0.060
          age
                          -2.0263
                                         0.531
                                                    -3.815
                                                                  0.000
                                                                              -3.067
                                                                                            -0.985
          sex
                           0.8986
                                                                  0.000
                                         0.223
                                                     4.027
                                                                               0.461
                                                                                             1.336
          cp
```

#### #BUILDING THE RANDOMFOREST AND CALCULATING THE ACCURACY

#### **SCREENSHOT:**

```
n [90]: # Building the Randomforest model
        from sklearn.ensemble import RandomForestClassifier
        clf=RandomForestClassifier(criterion='gini',
                                   max_depth=7,
                                   n_estimators=200,
                                   #min_samples_split=10,
                                   random_state=5)
n [91]: #fitting the model
        clf.fit(X_train,y_train)
ut[91]:
                                 RandomForestClassifier
         RandomForestClassifier(max_depth=7, n_estimators=200, random_state=5)
n [92]: y_predt=clf.predict(X_test)
n [93]: clf.feature_importances_
ut[93]: array([0.07794457, 0.05003741, 0.15391964, 0.06958547, 0.07236738, 0.01105043, 0.0165406, 0.11611831, 0.05549952, 0.11698825, 0.04239796, 0.11501138, 0.1025391])
n [95]: heathcare_df.columns
n [96]: from sklearn.metrics import confusion_matrix
        confusion_matrix(y_test,y_predt)
ut[96]: array([[25, 8]
               [ 3, 40]])
n [99]: accuracy_score(y_test,y_predt)*100
ut[99]: 85.52631578947368
```