

DATA PRE-PROCESSING

IMPORTING LIBRARIES

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import r2_score
from sklearn.metrics import accuracy_score
```

```
In [ ]:
```

IMPORTING DATASET

```
In [2]: df=pd.read_csv("Chronic_Kidney_Disease.csv") #IMPORTED CHRONIC_KIDNEY_D
ISEASE FILE
```

EXPLORING THE DATA

```
In [3]: df
```

Out[3]:

	id	age	bp	sg	al	su	rbc	pc	pcc	ba	...	pcv	wc	r
0	0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	...	44	7800	5.2
1	1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	...	38	6000	NaN
2	2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	...	31	7500	NaN
3	3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	...	32	6700	3.9
4	4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	...	35	7300	4.6
...
395	395	55.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	47	6700	4.6
396	396	42.0	70.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	54	7800	6.0
397	397	12.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	49	6600	5.2
398	398	17.0	60.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	51	7200	5.2
399	399	58.0	80.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	53	6800	6.0

400 rows × 26 columns



In [4]: df.head()

Out[4]:

	id	age	bp	sg	al	su	rbc	pc	pcc	ba	...	pcv	wc	rc	h
0	0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	...	44	7800	5.2	y
1	1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	...	38	6000	NaN	
2	2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	...	31	7500	NaN	
3	3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	...	32	6700	3.9	y
4	4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	...	35	7300	4.6	

5 rows × 26 columns



In [5]: df.tail()

Out[5]:

	id	age	bp	sg	al	su	rbc	pc	pcc	ba	...	pcv	wc	rc	t
395	395	55.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	47	6700	4.9	
396	396	42.0	70.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	54	7800	6.2	
397	397	12.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	49	6600	5.4	
398	398	17.0	60.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	51	7200	5.9	
399	399	58.0	80.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	53	6800	6.1	

5 rows × 26 columns

In [6]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 26 columns):
#   Column          Non-Null Count  Dtype
---  -
0   id               400 non-null   int64
1   age              391 non-null   float64
2   bp               388 non-null   float64
3   sg               353 non-null   float64
4   al               354 non-null   float64
5   su               351 non-null   float64
6   rbc              248 non-null   object
7   pc               335 non-null   object
8   pcc              396 non-null   object
9   ba               396 non-null   object
10  bgr              356 non-null   float64
11  bu               381 non-null   float64
12  sc               383 non-null   float64
13  sod              313 non-null   float64
14  pot              312 non-null   float64
15  hemo             348 non-null   float64
16  pcv              330 non-null   object
17  wc               295 non-null   object
```

```

18 rc 270 non-null object
19 htn 398 non-null object
20 dm 398 non-null object
21 cad 398 non-null object
22 appet 399 non-null object
23 pe 399 non-null object
24 ane 399 non-null object
25 classification 400 non-null object
dtypes: float64(11), int64(1), object(14)
memory usage: 81.4+ KB

```

In [7]: `df.describe()`

Out[7]:

	id	age	bp	sg	al	su	bgr	
count	400.000000	391.000000	388.000000	353.000000	354.000000	351.000000	356.000000	381.000000
mean	199.500000	51.483376	76.469072	1.017408	1.016949	0.450142	148.036517	57.469072
std	115.614301	17.169714	13.683637	0.005717	1.352679	1.099191	79.281714	50.914301
min	0.000000	2.000000	50.000000	1.005000	0.000000	0.000000	22.000000	1.005000
25%	99.750000	42.000000	70.000000	1.010000	0.000000	0.000000	99.000000	27.000000
50%	199.500000	55.000000	80.000000	1.020000	0.000000	0.000000	121.000000	42.000000
75%	299.250000	64.500000	80.000000	1.020000	2.000000	0.000000	163.000000	66.000000
max	399.000000	90.000000	180.000000	1.025000	5.000000	5.000000	490.000000	391.000000

In [8]: `df.isnull().any()`

Out[8]:

id	False
age	True
bp	True
sg	True
al	True
su	True
rbc	True
pc	True

```
pcc      True
ba       True
bgr      True
bu       True
sc       True
sod      True
pot      True
hemo     True
pcv      True
wc       True
rc       True
htn      True
dm       True
cad      True
appet    True
pe       True
ane      True
classification False
dtype: bool
```

```
In [9]: df.shape
```

```
Out[9]: (400, 26)
```

```
In [ ]:
```

handling missing data

```
In [10]: df.isnull().any()
```

```
Out[10]: id      False
age      True
bp       True
sg       True
al       True
```

```

su                True
rbc               True
pc               True
pcc              True
ba               True
bgr             True
bu              True
sc              True
sod             True
pot            True
hemo            True
pcv            True
wc             True
rc             True
htn            True
dm             True
cad            True
appet          True
pe             True
ane            True
classification    False
dtype: bool

```

```

In [11]: #Create a list of columns to retain
columns_to_retain = ["sg", "al", "sc", "hemo",
                    "pcv", "wbcc", "rbcc", "htn", "classification"]

#columns_to_retain = df.columns, Drop the columns that are not in columns_to_retain
df = df.drop([col for col in df.columns if not col in columns_to_retain], axis=1)

# Drop the rows with na or missing values
df = df.dropna(axis=0)
df

```

```

Out[11]:
   sg  al  sc  hemo  pcv  htn  classification

```

0	1.020	1.0	1.2	15.4	44	yes	ckd
1	1.020	4.0	0.8	11.3	38	no	ckd
	sg	al	sc	hemo	pcv	htn	classification
2	1.010	2.0	1.8	9.6	31	no	ckd
3	1.005	4.0	3.8	11.2	32	yes	ckd
4	1.010	2.0	1.4	11.6	35	no	ckd
...
395	1.020	0.0	0.5	15.7	47	no	notckd
396	1.025	0.0	1.2	16.5	54	no	notckd
397	1.020	0.0	0.6	15.8	49	no	notckd
398	1.025	0.0	1.0	14.2	51	no	notckd
399	1.025	0.0	1.1	15.8	53	no	notckd

287 rows × 7 columns

taking care of missing data

```
In [12]: df.shape
df["sg"].fillna(df["sg"].mean(), inplace=True)
df["al"].fillna(df["al"].mean(), inplace=True)
df["sc"].fillna(df["sc"].mean(), inplace=True)
df["hemo"].fillna(df["hemo"].mean(), inplace=True)
df["pcv"].fillna(df["pcv"].median(), inplace=True)
df.isnull().any()
```

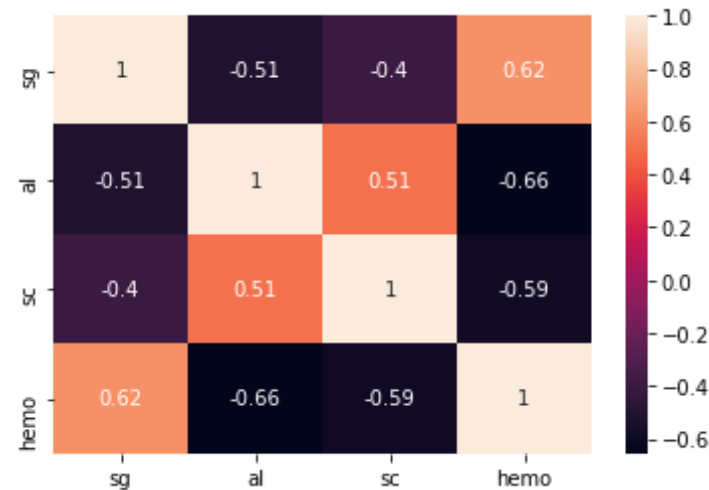
```
Out[12]: sg                False
al                False
sc                False
hemo              False
pcv               False
htn               False
```

```
classification    False
dtype: bool
```

data visualization (before prediction)

```
In [13]: sb.heatmap(df.corr(),annot=True)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x25da6a28c88>
```

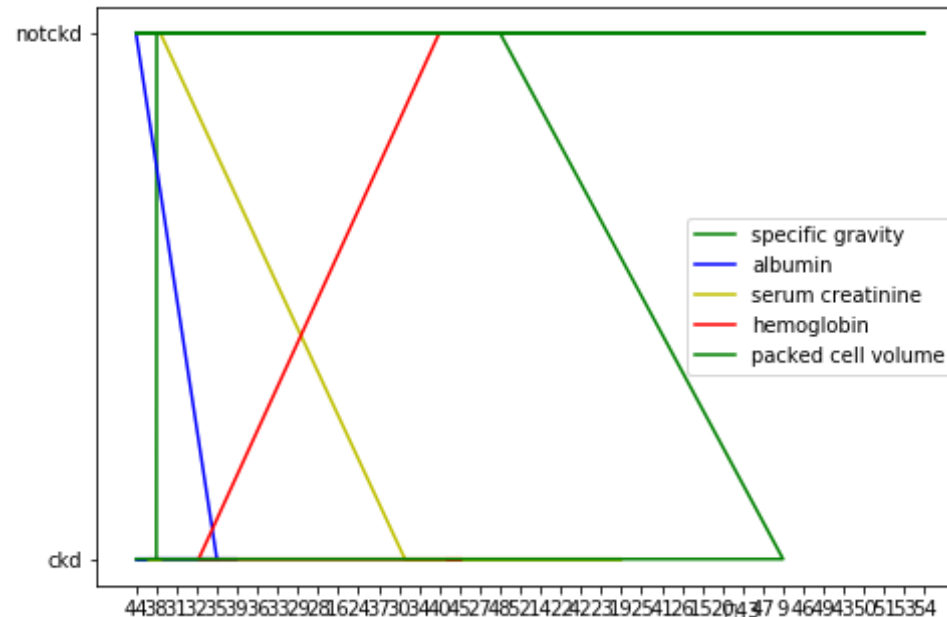


```
In [14]: fig1=plt.figure()
ax=fig1.add_axes([0,0,1,1])
ax.plot(df['sg'],df['classification'],color='g',label='specific gravit
y')#starting green line
ax.plot(df['al'],df['classification'],color='b',label='albumin')
ax.plot(df['sc'],df['classification'],color='y',label='serum creatinin
e')
ax.plot(df['hemo'],df['classification'],color='r',label='hemoglobin')
ax.plot(df['pcv'],df['classification'],color='g',label='packed cell vol
ume')
ax.legend()
```

```
Out[14]: <matplotlib.legend.Legend at 0x25da720d748>
```

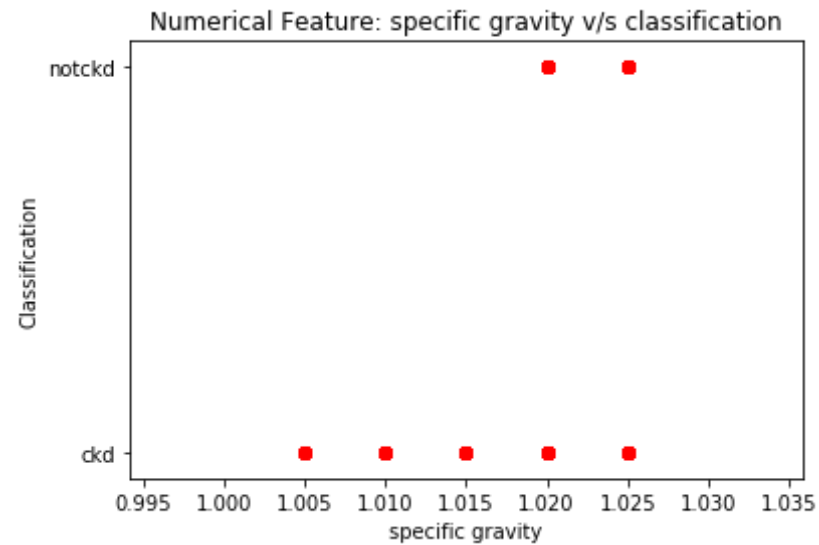


```
C:\Users\MARRIPELLI SAIKIRAN\anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py:211: RuntimeWarning: Glyph 9 missing from current font.
  font.set_text(s, 0.0, flags=flags)
C:\Users\MARRIPELLI SAIKIRAN\anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py:180: RuntimeWarning: Glyph 9 missing from current font.
  font.set_text(s, 0, flags=flags)
```



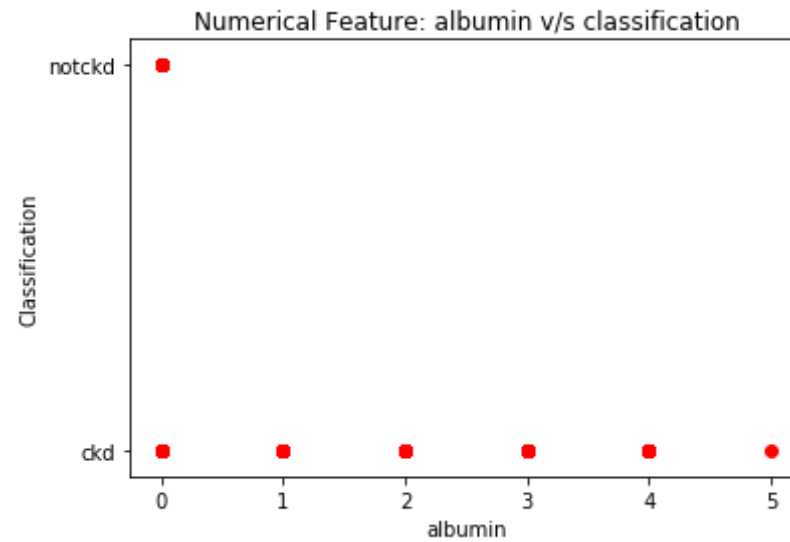
```
In [15]: plt.scatter(df['sg'], df['classification'],color='red')
plt.title('Numerical Feature: specific gravity v/s classification')
plt.xlabel('specific gravity')
plt.ylabel('Classification')
```

```
Out[15]: Text(0, 0.5, 'Classification')
```



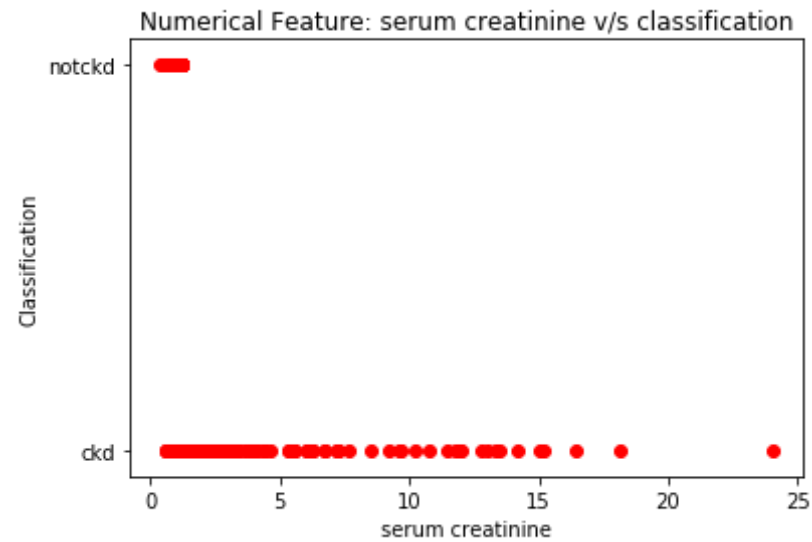
```
In [16]: plt.scatter(df['al'], df['classification'],color='red')
plt.title('Numerical Feature: albumin v/s classification')
plt.xlabel('albumin')
plt.ylabel('Classification')
```

```
Out[16]: Text(0, 0.5, 'Classification')
```



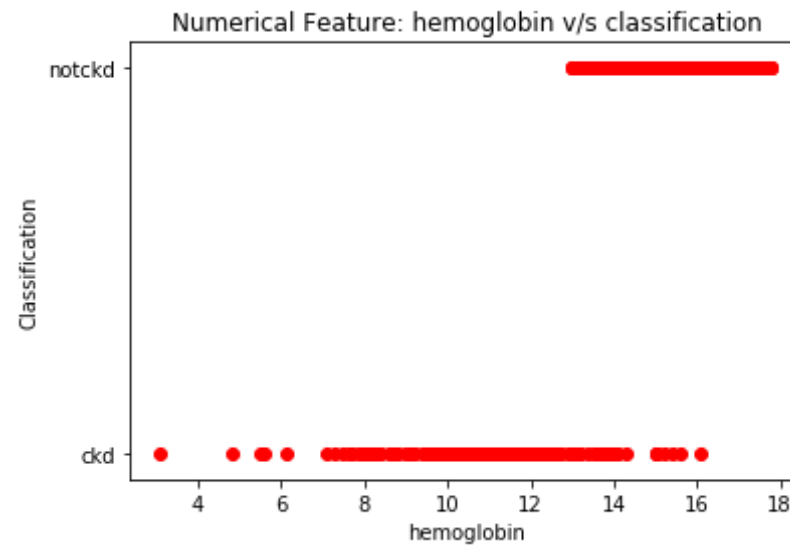
```
In [17]: plt.scatter(df['sc'], df['classification'],color='red')
plt.title('Numerical Feature: serum creatinine v/s classification')
plt.xlabel('serum creatinine')
plt.ylabel('Classification')
```

```
Out[17]: Text(0, 0.5, 'Classification')
```



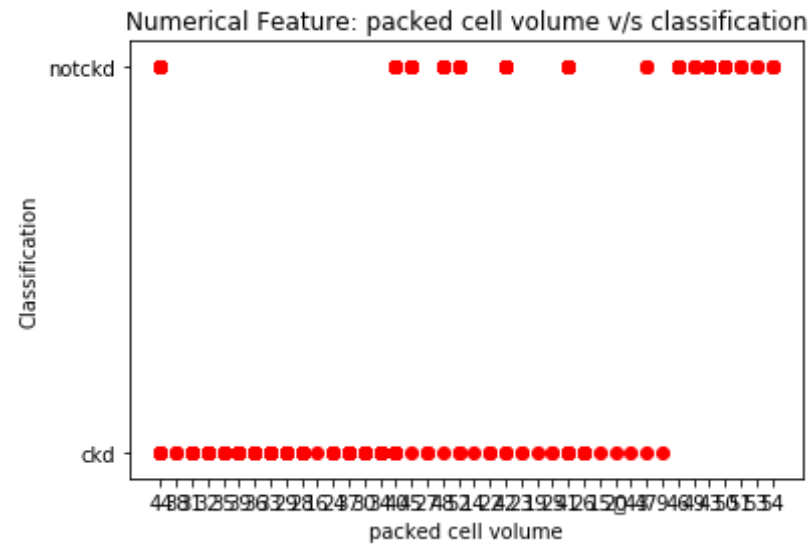
```
In [18]: plt.scatter(df['hemo'], df['classification'],color='red')
plt.title('Numerical Feature: hemoglobin v/s classification')
plt.xlabel('hemoglobin')
plt.ylabel('Classification')
```

```
Out[18]: Text(0, 0.5, 'Classification')
```



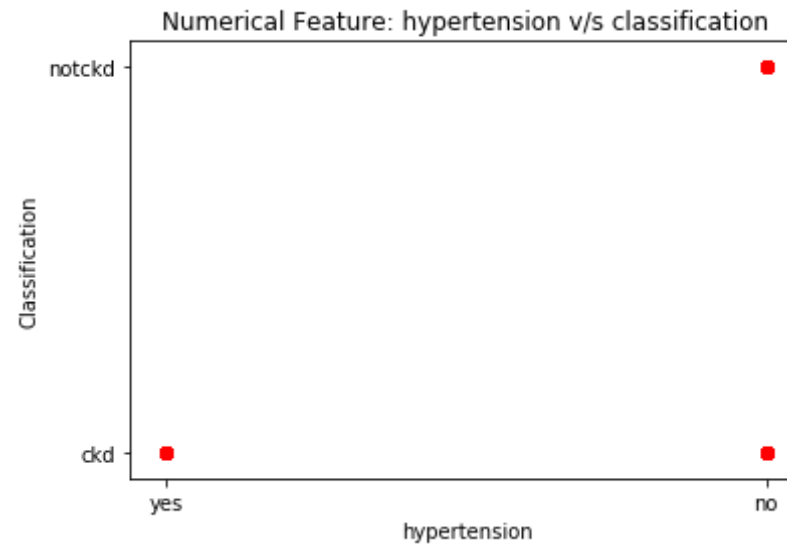
```
In [19]: plt.scatter(df['pcv'], df['classification'],color='red')
plt.title('Numerical Feature: packed cell volume v/s classification')
plt.xlabel('packed cell volume')
plt.ylabel('Classification')
```

```
Out[19]: Text(0, 0.5, 'Classification')
```



```
In [20]: plt.scatter(df['htn'], df['classification'],color='red')
plt.title('Numerical Feature: hypertension v/s classification')
plt.xlabel('hypertension')
plt.ylabel('Classification')
```

```
Out[20]: Text(0, 0.5, 'Classification')
```



separating data into dependent and independent

```
In [21]: x = df.iloc[:,0:6].values  
x
```

```
Out[21]: array([[1.02, 1.0, 1.2, 15.4, '44', 'yes'],  
               [1.02, 4.0, 0.8, 11.3, '38', 'no'],  
               [1.01, 2.0, 1.8, 9.6, '31', 'no'],  
               ...,  
               [1.02, 0.0, 0.6, 15.8, '49', 'no'],  
               [1.025, 0.0, 1.0, 14.2, '51', 'no'],  
               [1.025, 0.0, 1.1, 15.8, '53', 'no']], dtype=object)
```

```
In [22]: y=df.iloc[:,6:].values  
y
```

```
Out[22]: array(['ckd'],  
               ['ckd'],
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd'],  
['notckd']], dtype=object)
```

In []:

one hot encoding

```
In [23]: ct=ColumnTransformer([("on",OneHotEncoder(),[5])],remainder="passthroug  
h")  
x=ct.fit_transform(x)  
x
```

```
Out[23]: array([[0.0, 1.0, 1.02, ..., 1.2, 15.4, '44'],  
[1.0, 0.0, 1.02, ..., 0.8, 11.3, '38'],  
[1.0, 0.0, 1.01, ..., 1.8, 9.6, '31'],  
...,  
[1.0, 0.0, 1.02, ..., 0.6, 15.8, '49'],  
[1.0, 0.0, 1.025, ..., 1.0, 14.2, '51'],  
[1.0, 0.0, 1.025, ..., 1.1, 15.8, '53']], dtype=object)
```

removing dummy variables in x

```
In [24]: x=x[:,1:]  
x
```

```
Out[24]: array([[1.0, 1.02, 1.0, 1.2, 15.4, '44'],
               [0.0, 1.02, 4.0, 0.8, 11.3, '38'],
               [0.0, 1.01, 2.0, 1.8, 9.6, '31'],
               ...,
               [0.0, 1.02, 0.0, 0.6, 15.8, '49'],
               [0.0, 1.025, 0.0, 1.0, 14.2, '51'],
               [0.0, 1.025, 0.0, 1.1, 15.8, '53']], dtype=object)
```

#label encoding

```
In [25]: le=LabelEncoder()
         y=le.fit_transform(y)
         y
```

```
C:\Users\MARRIPELLI SAIKIRAN\anaconda3\lib\site-packages\sklearn\prepro-
cessing\_label.py:251: DataConversionWarning: A column-vector y was pas-
sed when a 1d array was expected. Please change the shape of y to (n_sa-
mples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
Out[25]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0,
               0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
               1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
               1])
```



```

1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
1])

```

feature scaling

In [26]: `""" MIN MAX SCALER """`

```

min_max_scaler = preprocessing.MinMaxScaler(feature_range=(0, 1))

# Scaled feature
x= min_max_scaler.fit_transform(x)
x.round()

```

Out[26]: `array([[1., 1., 0., 0., 1., 1.],
 [0., 1., 1., 0., 1., 1.],
 [0., 0., 0., 0., 0., 0.],
 ...,
 [0., 1., 0., 0., 1., 1.],
 [0., 1., 0., 0., 1., 1.],
 [0., 1., 0., 0., 1., 1.]])`

In []:

In []:

splitting the data into training and testing

sets

```
In [27]: x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,  
random_state=0)
```

APPLYING SUITABLE CLASSIFICATION ALGORITHM

```
In [28]: rfc = RandomForestClassifier (criterion = 'entropy', random_state = 0)
```

training and testing the model

```
In [29]: x_test
```

```
Out[29]: array([[1.        , 0.25        , 0.2        , 0.05932203, 0.70748299,  
0.68888889],  
[0.        , 1.        , 0.        , 0.00847458, 0.89795918,  
0.86666667],  
[1.        , 0.75        , 0.2        , 0.02542373, 0.50340136,  
0.51111111],  
[0.        , 0.75        , 0.        , 0.01271186, 0.68707483,  
0.77777778],  
[0.        , 0.75        , 0.        , 0.02118644, 0.91836735,  
0.75555556],  
[0.        , 0.5        , 0.2        , 0.24152542, 0.29931973,  
0.4        ],  
[0.        , 0.5        , 0.4        , 0.08898305, 0.68707483,  
0.71111111],  
[0.        , 0.75        , 0.        , 0.02118644, 0.97959184,  
0.68888889],  
[1.        , 1.        , 0.        , 0.03813559, 0.65306122,  
0.62222222],  
[1.        , 0.25        , 0.6        , 0.09745763, 0.63945578,  
0.62222222],
```

```

[0.          , 1.          , 0.          , 0.00423729, 0.91836735,
 0.68888889],
[0.          , 0.75       , 0.          , 0.00847458, 0.93197279,
 0.71111111],
[1.          , 0.5        , 0.6         , 0.0720339 , 0.44897959,
 0.42222222],
[1.          , 0.5        , 0.8         , 0.22033898, 0.34013605,
 0.31111111],
[0.          , 0.25       , 0.          , 0.05084746, 0.57823129,
 0.6         ],
[0.          , 0.75       , 0.          , 0.00423729, 0.92517007,
 0.95555556],
[0.          , 0.75       , 0.          , 0.00423729, 0.82312925,
 0.68888889],
[0.          , 0.75       , 0.          , 0.03389831, 0.68707483,
 0.71111111],
[0.          , 1.          , 0.          , 0.00847458, 0.68027211,
 0.8         ],
[0.          , 0.5        , 0.          , 0.01694915, 0.59183673,
 0.55555556],
[1.          , 0.25       , 0.8         , 0.54661017, 0.          ,
 0.          ],
[0.          , 0.75       , 0.          , 0.00423729, 0.71428571,
 0.77777778],
[1.          , 0.25       , 0.          , 0.06779661, 0.40136054,
 0.4         ],
[0.          , 0.75       , 0.          , 0.01694915, 0.74829932,
 0.8         ],
[1.          , 0.5        , 0.4         , 0.05508475, 0.63945578,
 0.53333333],
[0.          , 0.25       , 0.8         , 0.05508475, 0.3537415 ,
 0.31111111],
[0.          , 0.75       , 0.          , 0.02966102, 0.86394558,
 0.71111111],
[0.          , 0.75       , 0.          , 0.01694915, 1.          ,
 0.77777778],
[1.          , 0.5        , 0.          , 0.04661017, 0.3877551 ,
 0.35555556],
[0.          , 1.          , 0.          , 0.02966102, 0.86394558,

```

```

0.97777778],
[0.          , 1.          , 0.          , 0.01271186, 0.97278912,
0.95555556],
[1.          , 0.5         , 0.6         , 0.06355932, 0.52380952,
0.53333333],
[1.          , 0.5         , 0.6         , 0.02966102, 0.61904762,
0.66666667],
[0.          , 0.75        , 0.          , 0.02966102, 0.94557823,
0.91111111],
[1.          , 0.5         , 1.          , 0.53389831, 0.33333333,
0.33333333],
[0.          , 0.75        , 0.          , 0.00423729, 0.85714286,
0.84444444],
[0.          , 0.75        , 0.6         , 0.05932203, 0.54421769,
0.6         ],
[0.          , 0.75        , 0.          , 0.02118644, 0.65306122,
0.73333333],
[0.          , 0.5         , 0.4         , 0.02966102, 0.63265306,
0.77777778],
[0.          , 0.25        , 0.2         , 0.09745763, 0.55102041,
0.6         ],
[1.          , 0.25        , 0.6         , 0.16949153, 0.46938776,
0.51111111],
[0.          , 1.          , 0.          , 0.01694915, 0.67346939,
0.88888889],
[0.          , 1.          , 0.          , 0.02542373, 0.85714286,
0.91111111],
[0.          , 1.          , 0.          , 0.00847458, 0.73469388,
0.86666667],
[0.          , 0.75        , 0.          , 0.00847458, 0.71428571,
0.93333333],
[1.          , 0.25        , 0.6         , 0.48305085, 0.34013605,
0.33333333],
[0.          , 1.          , 0.          , 0.03389831, 0.83673469,
0.73333333],
[0.          , 1.          , 0.          , 0.02966102, 0.72108844,
0.8         ],
[0.          , 0.5         , 0.6         , 0.03389831, 0.52380952,
0.53333333],

```

```
[0.          , 0.75          , 0.          , 0.02966102, 0.83673469,
 0.73333333],
[1.          , 0.25          , 0.4          , 0.11864407, 0.67346939,
 0.68888889],
[0.          , 1.          , 0.          , 0.01271186, 0.67346939,
 1.          ],
[0.          , 0.75          , 0.          , 0.00847458, 0.91156463,
 0.95555556],
[0.          , 1.          , 0.          , 0.02542373, 0.82993197,
 0.77777778],
[0.          , 0.75          , 0.          , 0.03813559, 0.63945578,
 0.62222222],
[1.          , 0.75          , 0.4          , 0.08474576, 0.70068027,
 0.84444444],
[0.          , 1.          , 0.          , 0.01271186, 0.79591837,
 0.8          ],
[1.          , 1.          , 0.          , 0.06355932, 0.46258503,
 0.44444444]])
```

In [30]: x_train

```
Out[30]: array([[0.          , 0.25          , 0.2          , 0.02966102, 0.80952381,
 0.86666667],
 [0.          , 0.75          , 0.          , 0.03389831, 0.89115646,
 0.91111111],
 [0.          , 0.75          , 0.          , 0.03389831, 0.85714286,
 0.77777778],
 ...,
 [1.          , 0.5          , 0.6          , 0.12288136, 0.55782313,
 0.48888889],
 [0.          , 0.25          , 0.4          , 0.12288136, 0.53061224,
 0.62222222],
 [0.          , 1.          , 0.          , 0.02118644, 0.73469388,
 0.86666667]])
```

In [31]: y_test

```
Out[31]: array([0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0,
 1,
```

```
0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1,
1,
1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0])
```

```
In [32]: y_train
```

```
Out[32]: array([0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
0,
1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0,
1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,
0,
0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1,
1,
0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0,
1,
1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1,
1,
0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0,
1,
0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0,
0,
0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0,
0,
1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0,
1,
1, 1, 0, 1, 1, 1, 0, 0, 1])
```

```
In [33]: rfc.fit(x_train,y_train)
```

```
Out[33]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
criterion='entropy', max_depth=None, max_features='auto',
max_leaf_nodes=None, max_samples=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=100,
```

```
                                n_jobs=None, oob_score=False, random_state=0, ve  
rbose=0,  
                                warm_start=False)
```

```
In [34]: rfc.predict(x_test)
```

```
Out[34]: array([0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0,  
1,  
            0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1,  
1,  
            1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0])
```

```
In [35]: y_pred=rfc.predict(x_test)  
y_pred
```

```
Out[35]: array([0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0,  
1,  
            0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1,  
1,  
            1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0])
```

```
In [36]: x_train.shape
```

```
Out[36]: (229, 6)
```

evaluation metrics

```
In [37]: r2_score(y_test,y_pred)
```

```
Out[37]: 0.9310344827586207
```

```
In [38]: accuracy_score(y_test,y_pred)
```

```
Out[38]: 0.9827586206896551
```

In []:

In []:

In []:

In []:

In []:

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In []: