### SPRINT 2 - TEAM ID PNT2022TMID12917

**DATE: 12th November 2022** 

**Topic: Early Detection of Chronic Kidney Disease using Machine Learning** 

## **MODEL BUILDING**

## 1. Importing the necessary libraries

```
In [64]:
```

```
import pandas as pd
import numpy as mp
from collections import Counter as c
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
import pickle
```

## 2. Loading the Dataset

```
In [90]:
```

data=pd.read\_csv(r"C:\Users\archa\Desktop\IBM Datasets\chronickidneydisease.csv")

```
In [91]:
```

```
data.head(5)
```

#### Out[91]:

	id	age	bp	sg	al	su	rbc	рс	рсс	ba	•••	pcv	wc	rc
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	norma <b>l</b>	notpresent	notpresent		38	6000	NaN
2	2	62.0	0.08	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	abnorma <b>l</b>	present	notpresent		32	6700	3.9
4	4	51.0	0.08	1.010	2.0	0.0	normal	normal	notpresent	notpresent		35	7300	4.6

5 rows × 26 columns

**→** 

#### In [92]:

```
data.tail(5)
```

#### Out[92]:

	id	age	bp	sg	al	su	rbc	рс	рсс	ba	•••	pcv	wc	rc
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	0.08	1.025	0.0	0.0	normal	normal	notpresent	notpresent		53	6800	6.1

5 rows × 26 columns

**→** 

#### In [93]:

```
data.drop(["id"],axis=1,inplace=True)
```

#### In [94]:

```
data.columns
```

#### Out[94]:

```
In [95]:
```

```
ta.columns=['age', 'blood_pressure', 'specific_gravity', 'albumin', 'sugar', 'red_blood_cell 'serum_creatinine', 'sodium', 'potassium', 'hemoglobin', 'packed_cell_volume', 'white_k 'appetite', 'pedal_edema', 'anemia', 'class']
```

#### In [96]:

```
data.columns
```

#### Out[96]:

## 3. Understanding Data Type And Summary Of Features

```
In [97]:
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 25 columns):
#
     Column
                               Non-Null Count Dtype
0
     age
                               391 non-null
                                                float64
1
     blood_pressure
                               388 non-null
                                                float64
 2
     specific gravity
                               353 non-null
                                                float64
                               354 non-null
 3
     albumin
                                                float64
 4
     sugar
                               351 non-null
                                                float64
 5
     red blood cells
                               248 non-null
                                                object
 6
                               335 non-null
                                                object
     pus_cell
 7
     pus_cell_clumps
                               396 non-null
                                                object
 8
     bacteria
                               396 non-null
                                                object
 9
     blood glucose random
                                                float64
                               356 non-null
 10
     blood urea
                               381 non-null
                                                float64
 11
     serum creatinine
                               383 non-null
                                                float64
                               313 non-null
 12
     sodium
                                                float64
 13
     potassium
                               312 non-null
                                                float64
 14
    hemoglobin
                               348 non-null
                                                float64
     packed_cell_volume
                               330 non-null
                                                object
                                                object
     white_blood_cell_count
                               295 non-null
 17
     red_blood_cell_count
                               270 non-null
                                                object
 18
     hypertension
                               398 non-null
                                                object
 19
     diabetesmellitus
                               398 non-null
                                                object
 20
    coronary_artery_disease 398 non-null
                                                object
                               399 non-null
                                                object
 21
     appetite
 22
     pedal edema
                               399 non-null
                                                object
 23
     anemia
                               399 non-null
                                                object
    class
                               400 non-null
                                                object
```

dtypes: float64(11), object(14)

memory usage: 78.2+ KB

## **Target Column**

```
In [98]:
data['class'].unique()
Out[98]:
array(['ckd', 'ckd\t', 'notckd'], dtype=object)
```

## Rectifying the target column

```
In [99]:
data['class']=data['class'].replace("ckd\t","ckd")
data['class'].unique()
Out[99]:
array(['ckd', 'notckd'], dtype=object)
```

## **Categorical Columns**

#### In [100]:

```
catcols=set(data.dtypes[data.dtypes=='0'].index.values)
print(catcols)
```

```
{'class', 'packed_cell_volume', 'red_blood_cells', 'pus_cell', 'appetite',
'bacteria', 'pedal_edema', 'hypertension', 'red_blood_cell_count', 'white_bl
ood_cell_count', 'anemia', 'diabetesmellitus', 'coronary_artery_disease', 'p
us_cell_clumps'}
```

#### In [101]:

```
for i in catcols:
   print("Columns :",i)
   print(c(data[i]))
   print('*'*120+'\n')
Columns : class
Counter({'ckd': 250, 'notckd': 150})
********************************
**************
Columns : packed cell volume
Counter({nan: 70, '52': 21, '41': 21, '44': 19, '48': 19, '40': 16, '43': 1
4, '45': 13, '42': 13, '32': 12, '36': 12, '33': 12, '28': 12, '50': 12, '3
7': 11, '34': 11, '35': 9, '29': 9, '30': 9, '46': 9, '31': 8, '39': 7, '2
4': 7, '26': 6, '38': 5, '47': 4, '49': 4, '53': 4, '51': 4, '54': 4, '27':
3, '22': 3, '25': 3, '23': 2, '19': 2, '16': 1, '\t?': 1, '14': 1, '18': 1,
'17': 1, '15': 1, '21': 1, '20': 1, '\t43': 1, '9': 1})
**********************************
*************
Columns : red blood cells
Counter({'normal': 201, nan: 152, 'abnormal': 47})
***********************************
**************
Columns : pus_cell
Counter({'normal': 259, 'abnormal': 76, nan: 65})
******************************
****************
Columns : appetite
Counter({'good': 317, 'poor': 82, nan: 1})
**************
Columns : bacteria
Counter({'notpresent': 374, 'present': 22, nan: 4})
*************
Columns : pedal edema
Counter({'no': 323, 'yes': 76, nan: 1})
************************************
Columns : hypertension
Counter({'no': 251, 'yes': 147, nan: 2})
*************
Columns : red blood cell count
Counter({nan: 130, '5.2': 18, '4.5': 16, '4.9': 14, '4.7': 11, '3.9': 10, '4.8': 10, '4.6': 9, '3.4': 9, '3.7': 8, '5.0': 8, '6.1': 8, '5.5': 8, '5.
9': 8, '3.8': 7, '5.4': 7, '5.8': 7, '5.3': 7, '4.3': 6, '4.2': 6, '5.6': 6,
'4.4': 5, '3.2': 5, '4.1': 5, '6.2': 5, '5.1': 5, '6.4': 5, '5.7': 5, '6.5':
5, '3.6': 4, '6.0': 4, '6.3': 4, '4.0': 3, '4': 3, '3.5': 3, '3.3': 3, '5':
2, '2.6': 2, '2.8': 2, '2.5': 2, '3.1': 2, '2.1': 2, '2.9': 2, '2.7': 2, '3.
0': 2, '2.3': 1, '8.0': 1, '3': 1, '2.4': 1, '\t?': 1})
```

\*\*\*\*\*\*\*\*\*\*\*\*\*

```
Columns : white blood cell count
Counter({nan: 105, '9800': 11, '6700': 10, '9600': 9, '9200': 9, '7200': 9,
'6900': 8, '11000': 8, '5800': 8, '7800': 7, '9100': 7, '9400': 7, '7000':
7, '4300': 6, '6300': 6, '10700': 6, '10500': 6, '7500': 5, '8300': 5, '790
0': 5, '8600': 5, '5600': 5, '10200': 5, '5000': 5, '8100': 5, '9500': 5, '6
000': 4, '6200': 4, '10300': 4, '7700': 4, '5500': 4, '10400': 4, '6800': 4,
'6500': 4, '4700': 4, '7300': 3, '4500': 3, '8400': 3, '6400': 3, '4200': 3,
'7400': 3, '8000': 3, '5400': 3, '3800': 2, '11400': 2, '5300': 2, '8500':
2, '14600': 2, '7100': 2, '13200': 2, '9000': 2, '8200': 2, '15200': 2, '124
00': 2, '12800': 2, '8800': 2, '5700': 2, '9300': 2, '6600': 2, '12100': 1,
'12200': 1, '18900': 1, '21600': 1, '11300': 1, '\t6200': 1, '11800': 1, '12
500': 1, '11900': 1, '12700': 1, '13600': 1, '14900': 1, '16300': 1, '\t840
0': 1, '10900': 1, '2200': 1, '11200': 1, '19100': 1, '\t?': 1, '12300': 1,
'16700': 1, '2600': 1, '26400': 1, '4900': 1, '12000': 1, '15700': 1, '410
0': 1, '11500': 1, '10800': 1, '9900': 1, '5200': 1, '5900': 1, '9700': 1,
'5100': 1})
********************************
***************
Columns : anemia
Counter({'no': 339, 'yes': 60, nan: 1})
***********************************
****************
Columns : diabetesmellitus
Counter({'no': 258, 'yes': 134, '\tno': 3, '\tyes': 2, nan: 2, ' yes': 1})
***********************************
****************
Columns : coronary_artery_disease
Counter({'no': 362, 'yes': 34, '\tno': 2, nan: 2})
******************************
***************
Columns : pus_cell_clumps
Counter({'notpresent': 354, 'present': 42, nan: 4})
***************
```

# 4. Understanding Data Type And Summary Of Features

Removing the Columns which are not Categorical

```
In [102]:
```

```
catcols.remove('red_blood_cell_count')
catcols.remove('packed_cell_volume')
catcols.remove('white_blood_cell_count')
print(catcols)

{'class', 'red_blood_cells', 'pus_cell', 'appetite', 'bacteria', 'pedal_edem
a', 'hypertension', 'anemia', 'diabetesmellitus', 'coronary_artery_disease',
'pus_cell_clumps'}
```

#### **Numerical Columns**

```
In [103]:
```

```
contcols=set(data.dtypes[data.dtypes!='0'].index.values)
print(contcols)
{'blood_urea', 'age', 'potassium', 'hemoglobin', 'sodium', 'sugar',
n', 'blood glucose random', 'specific_gravity', 'serum_creatinine', 'blood_p
ressure'}
In [104]:
for i in contcols:
    print("Continuous Columns :",i)
    print(c(data[i]))
   print('*'*120+'\n')
CONCINGOUS COTUMNIS . DIOOG SIGCOSE FANGOM
Counter({99.0: 10, 100.0: 9, 93.0: 9, 107.0: 8, 117.0: 6, 140.0: 6, 92.0:
6, 109.0: 6, 131.0: 6, 130.0: 6, 70.0: 5, 114.0: 5, 95.0: 5, 123.0: 5, 12
4.0: 5, 102.0: 5, 132.0: 5, 104.0: 5, 125.0: 5, 122.0: 5, 121.0: 4, 106.0:
4, 76.0: 4, 91.0: 4, 129.0: 4, 133.0: 4, 94.0: 4, 88.0: 4, 118.0: 4, 139.
0: 4, 111.0: 4, 113.0: 4, 120.0: 4, 119.0: 4, 74.0: 3, 108.0: 3, 171.0: 3,
137.0: 3, 79.0: 3, 150.0: 3, 112.0: 3, 127.0: 3, 219.0: 3, 172.0: 3, 89.0:
3, 128.0: 3, 214.0: 3, 105.0: 3, 78.0: 3, 103.0: 3, 82.0: 3, 97.0: 3, 81.
0: 3, 138.0: 2, 490.0: 2, 208.0: 2, 98.0: 2, 204.0: 2, 207.0: 2, 144.0: 2,
253.0: 2, 141.0: 2, 86.0: 2, 360.0: 2, 163.0: 2, 158.0: 2, 165.0: 2, 169.
0: 2, 210.0: 2, 101.0: 2, 153.0: 2, 213.0: 2, 424.0: 2, 303.0: 2, 192.0:
2, 80.0: 2, 110.0: 2, 96.0: 2, 85.0: 2, 83.0: 2, 75.0: 2, nan: 1, 423.0:
1, 410.0: 1, 380.0: 1, 157.0: 1, 263.0: 1, 173.0: 1, nan: 1, nan: 1, nan:
1, 156.0: 1, 264.0: 1, nan: 1, 159.0: 1, 270.0: 1, nan: 1, nan: 1, nan: 1,
162.0: 1, nan: 1, 246.0: 1, nan: 1, nan: 1, nan: 1, nan: 1, 182.0: 1, 146.
0: 1, nan: 1, 425.0: 1, 250.0: 1, nan: 1, nan: 1, nan: 1, 415.0: 1, 251.0:
1, 280.0: 1, 295.0: 1, 298.0: 1, 226.0: 1, 143.0: 1, 115.0: 1, 297.0: 1, 2
33.0: 1, 294.0: 1, nan: 1, nan: 1, nan: 1, nan: 1, 323.0: 1, nan: 1, nan:
1, 90.0: 1, 308.0: 1, 224.0: 1, nan: 1, 268.0: 1, nan: 1, 256.0: 1, nan:
1, 84.0: 1, nan: 1, 288.0: 1, 273.0: 1, 242.0: 1, 148.0: 1, nan: 1, 160.0:
```

#### Removing the Columns which are not Numerical

#### In [105]:

```
contcols.remove('specific_gravity')
contcols.remove('albumin')
contcols.remove('sugar')
print(contcols)
```

{'blood\_urea', 'age', 'potassium', 'hemoglobin', 'sodium', 'blood glucose ra ndom', 'serum\_creatinine', 'blood\_pressure'}

## 5. Understanding Data Type And Summary Of Features

#### Adding the Columns which are continuous

#### In [106]:

```
contcols.add('red_blood_cell_count')
contcols.add('packed_cell_volume')
contcols.add('white_blood_cell_count')
print(contcols)
```

```
{'blood_urea', 'packed_cell_volume', 'age', 'potassium', 'hemoglobin', 'sodi
um', 'blood glucose random', 'red_blood_cell_count', 'white_blood_cell_coun
t', 'serum_creatinine', 'blood_pressure'}
```

#### Adding the Columns which are categorical

#### In [107]:

```
catcols.add('specific_gravity')
catcols.add('albumin')
catcols.add('sugar')
print(catcols)
```

```
{'class', 'red_blood_cells', 'pus_cell', 'appetite', 'bacteria', 'albumin',
'pedal_edema', 'sugar', 'hypertension', 'anemia', 'specific_gravity', 'diabe
tesmellitus', 'coronary_artery_disease', 'pus_cell_clumps'}
```

#### Rectification of categorical columns

#### In [108]:

```
data['coronary_artery_disease']=data.coronary_artery_disease.replace('\tno','no')
c(data['coronary_artery_disease'])
```

#### Out[108]:

```
Counter({'no': 364, 'yes': 34, nan: 2})
```

```
In [109]:
```

```
data['diabetesmellitus']=data.diabetesmellitus.replace(to_replace={'\tno':'no','\tyes':'yes
c(data['diabetesmellitus'])
```

#### Out[109]:

```
Counter({'yes': 136, 'no': 261, ' yes': 1, nan: 2})
```

## 6. Handling the Missing Values

#### In [110]:

```
data.isnull().any()
```

#### Out[110]:

age	True
blood_pressure	True
specific_gravity	True
albumin	True
sugar	True
red_blood_cells	True
pus_cell	True
pus_cell_clumps	True
bacteria	True
blood glucose random	True
blood_urea	True
serum_creatinine	True
sodium	True
potassium	True
hemoglobin	True
packed_cell_volume	True
white_blood_cell_count	True
red_blood_cell_count	True
hypertension	True
diabetesmellitus	True
coronary_artery_disease	True
appetite	True
pedal_edema	True
anemia	True
class	False
dtype: bool	

#### In [111]:

```
data.isnull().sum()
Out[111]:
                               9
age
                              12
blood_pressure
                              47
specific_gravity
                              46
albumin
                              49
sugar
red_blood_cells
                             152
pus cell
                              65
                               4
pus_cell_clumps
bacteria
                               4
blood glucose random
                              44
                              19
blood_urea
serum_creatinine
                              17
sodium
                              87
                              88
potassium
hemoglobin
                              52
                              70
packed cell volume
white_blood_cell_count
                             105
red_blood_cell_count
                             130
hypertension
                               2
diabetesmellitus
                               2
                               2
coronary_artery_disease
appetite
                               1
                               1
pedal_edema
anemia
                               1
                               0
class
dtype: int64
In [112]:
```

```
data.packed_cell_volume = pd.to_numeric(data.packed_cell_volume, errors='coerce')
data.white_blood_cell_count = pd.to_numeric(data.white_blood_cell_count, errors='coerce')
data.red_blood_cell_count = pd.to_numeric(data.red_blood_cell_count, errors='coerce')
```

## 7. Replacing the Missing (Null) Values

#### In [113]:

```
data['blood glucose random'].fillna(data['blood glucose random'].mean(),inplace=True)
data['blood_pressure'].fillna(data['blood_pressure'].mean(),inplace=True)
data['blood_urea'].fillna(data['blood_urea'].mean(),inplace=True)
data['hemoglobin'].fillna(data['hemoglobin'].mean(),inplace=True)
data['packed_cell_volume'].fillna(data['packed_cell_volume'].mean(),inplace=True)
data['potassium'].fillna(data['potassium'].mean(),inplace=True)
data['red_blood_cell_count'].fillna(data['red_blood_cell_count'].mean(),inplace=True)
data['sodium'].fillna(data['sodium'].mean(),inplace=True)
data['white_blood_cell_count'].fillna(data['white_blood_cell_count'].mean(),inplace=True)
```

#### In [114]:

```
data['age'].fillna(data['age'].mode()[0],inplace=True)
data['hypertension'].fillna(data['hypertension'].mode()[0],inplace=True)
data['pus_cell_clumps'].fillna(data['pus_cell_clumps'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['albumin'].fillna(data['albumin'].mode()[0],inplace=True)
data['pus_cell'].fillna(data['pus_cell'].mode()[0],inplace=True)
data['red_blood_cells'].fillna(data['red_blood_cells'].mode()[0],inplace=True)
data['coronary_artery_disease'].fillna(data['coronary_artery_disease'].mode()[0],inplace=True)
data['anemia'].fillna(data['bacteria'].mode()[0],inplace=True)
data['sugar'].fillna(data['anemia'].mode()[0],inplace=True)
data['diabetesmellitus'].fillna(data['diabetesmellitus'].mode()[0],inplace=True)
data['pedal_edema'].fillna(data['pedal_edema'].mode()[0],inplace=True)
data['specific_gravity'].fillna(data['specific_gravity'].mode()[0],inplace=True)
```

#### In [115]:

```
data.isnull().any()
```

#### Out[115]:

age	False
blood_pressure	False
specific_gravity	False
albumin	False
sugar	False
red blood cells	False
pus_cell	False
pus_cell_clumps	False
bacteria	False
blood glucose random	False
blood_urea	False
serum_creatinine	False
sodium	False
potassium	False
hemoglobin	False
<pre>packed_cell_volume</pre>	False
white_blood_cell_count	False
red_blood_cell_count	False
hypertension	False
diabetesmellitus	False
coronary_artery_disease	False
appetite	False
pedal_edema	False
anemia	False
class	False
dtype: bool	

## 8. Label Encoding

#### In [116]:

```
for i in catcols:
  print("Label Encoding of: ",i)
  LEi = LabelEncoder()
  print(c(data[i]))
  data[i]=LEi.fit_transform(data[i])
  print(c(data[i]))
  print("*"*100)
Label Encoding of: class
Counter({'ckd': 250, 'notckd': 150})
Counter({0: 250, 1: 150})
*****************************
Label Encoding of: red_blood_cells
Counter({'normal': 353, 'abnormal': 47})
Counter({1: 353, 0: 47})
                *******************
********
Label Encoding of: pus_cell
Counter({'normal': 324, 'abnormal': 76})
Counter({1: 324, 0: 76})
*********
                 *******************
********
Label Encoding of: appetite
Counter({'good': 318, 'poor': 82})
Counter({0: 318, 1: 82})
*********************************
********
Label Encoding of: bacteria
Counter({'notpresent': 378, 'present': 22})
Counter({0: 378, 1: 22})
**********************************
********
Label Encoding of: albumin
Counter({0.0: 245, 1.0: 44, 2.0: 43, 3.0: 43, 4.0: 24, 5.0: 1})
Counter({0: 245, 1: 44, 2: 43, 3: 43, 4: 24, 5: 1})
******************************
********
Label Encoding of: pedal_edema
Counter({'no': 324, 'yes': 76})
Counter({0: 324, 1: 76})
                *********************
********
Label Encoding of: sugar
Counter({0.0: 339, 2.0: 18, 3.0: 14, 4.0: 13, 1.0: 13, 5.0: 3})
Counter({0: 339, 2: 18, 3: 14, 4: 13, 1: 13, 5: 3})
*********
Label Encoding of: hypertension
Counter({'no': 253, 'yes': 147})
Counter({0: 253, 1: 147})
************************************
Label Encoding of: anemia
Counter({'no': 340, 'yes': 60})
Counter({0: 340, 1: 60})
**********************************
*********
```

```
Label Encoding of: specific_gravity
Counter({1.02: 153, 1.01: 84, 1.025: 81, 1.015: 75, 1.005: 7})
Counter({3: 153, 1: 84, 4: 81, 2: 75, 0: 7})
********************************
*********
Label Encoding of: diabetesmellitus
Counter({'no': 263, 'yes': 136, ' yes': 1})
Counter({1: 263, 2: 136, 0: 1})
**********************************
Label Encoding of: coronary_artery_disease
Counter({'no': 366, 'yes': 34})
Counter({0: 366, 1: 34})
***********************************
********
Label Encoding of: pus_cell_clumps
Counter({'notpresent': 358, 'present': 42})
Counter({0: 358, 1: 42})
                  ***************
*********
```

# 9. Splitting The Dataset Into Dependent And Independent Variable

```
In [132]:

selcols=['red_blood_cells','pus_cell','blood glucose random','blood_urea','pedal_edema','an
x=pd.DataFrame(data,columns=selcols)
y=pd.DataFrame(data,columns=['class'])
print(x.shape)
print(y.shape)
```

10. Splitting The Dataset Into Train Set And Test Set

```
In [133]:
```

(400, 1)

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=2)
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)

(320, 8)
(320, 1)
(80, 8)
(80, 1)
```

## 11. Building a Machine Learning Model

```
In [146]:
```

```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression()
lgr.fit(x_train, y_train)

G:\Anaconda\lib\site-packages\sklearn\utils\validation.py:63: DataConversion
Warning: A column-vector y was passed when a 1d array was expected. Please c
hange the shape of y to (n_samples, ), for example using ravel().
    return f(*args, **kwargs)

Out[146]:
LogisticRegression()
```

### 12. Test the Model

```
In [151]:
```

## 13. Model Evaluation

## 14. Saving the Model

In [154]:
pickle.dump(lgr,open('CKD.pkl','wb'))
In [ ]: