## **Classification Assignment**

#### **Problem Statement & Requirement:**

A requirement from the Hospital, Management asked us to create a predictive model which will predict the Chronic Kidney Disease (CKD) based on the several parameters. The Client has provided the dataset of the same.

#### 1.) Identify your problem statement

We can find the problem statement by using 3 stage method

I. Data provided is numerically - Machine Learning

II. Input & Output Very clear - Supervised Learning

III. Output will be in categorical - Classification

### 2.) Basic info about the dataset (Total number of rows, columns)

Rows - 399 Columns - 25

# 3.) Mention the Pre-Processing method if you're doing any (like converting string to number – nominal data)

We used "ONE HOT ENCODING" to converting the string to number for the following column

pc\_normal pcc\_present ba\_present htn\_yes dm\_yes cad\_yes appet\_yes pe\_yes ane\_yes classification\_yes

#### 4.) Good evaluation metric is

Random forest the Accuracy is 0.99



```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]: dataset = pd.read\_csv('CKD.csv')
 dataset

	age	bp	sg	al	su	rbc	рс	рсс	ba	
0	2.000000	76.459948	С	3.0	0.0	normal	abnormal	notpresent	notpresent	1
1	3.000000	76.459948	С	2.0	0.0	normal	normal	notpresent	notpresent	1
2	4.000000	76.459948	а	1.0	0.0	normal	normal	notpresent	notpresent	
3	5.000000	76.459948	d	1.0	0.0	normal	normal	notpresent	notpresent	1
4	5.000000	50.000000	С	0.0	0.0	normal	normal	notpresent	notpresent	1
394	51.492308	70.000000	а	0.0	0.0	normal	normal	notpresent	notpresent	2
395	51.492308	70.000000	С	0.0	2.0	normal	normal	notpresent	notpresent	2
396	51.492308	70.000000	С	3.0	0.0	normal	normal	notpresent	notpresent	1
397	51.492308	90.000000	а	0.0	0.0	normal	normal	notpresent	notpresent	2
398	51.492308	80.000000	a	0.0	0.0	normal	normal	notpresent	notpresent	1
	1 2 3 4  394 395 396 397	0 2.000000 1 3.000000 2 4.000000 3 5.000000 4 5.000000 394 51.492308 395 51.492308 396 51.492308 397 51.492308	0       2.000000       76.459948         1       3.000000       76.459948         2       4.000000       76.459948         3       5.000000       76.459948         4       5.000000       50.000000              394       51.492308       70.000000         395       51.492308       70.000000         396       51.492308       90.000000	0       2.000000       76.459948       c         1       3.000000       76.459948       c         2       4.000000       76.459948       d         3       5.000000       76.459948       d         4       5.000000       50.000000       c               394       51.492308       70.000000       c         396       51.492308       70.000000       c         397       51.492308       90.000000       a	0       2.000000       76.459948       c       3.0         1       3.000000       76.459948       c       2.0         2       4.000000       76.459948       a       1.0         3       5.000000       76.459948       d       1.0         4       5.000000       50.000000       c       0.0                394       51.492308       70.000000       a       0.0         395       51.492308       70.000000       c       0.0         396       51.492308       70.000000       a       0.0         397       51.492308       90.000000       a       0.0	0       2.000000       76.459948       c       3.0       0.0         1       3.000000       76.459948       c       2.0       0.0         2       4.000000       76.459948       a       1.0       0.0         3       5.000000       76.459948       d       1.0       0.0         4       5.000000       50.000000       c       0.0       0.0                 394       51.492308       70.000000       a       0.0       0.0         395       51.492308       70.000000       c       3.0       0.0         396       51.492308       70.000000       a       0.0       0.0         397       51.492308       90.000000       a       0.0       0.0	0       2.000000       76.459948       c       3.0       0.0       normal         1       3.000000       76.459948       c       2.0       0.0       normal         2       4.000000       76.459948       d       1.0       0.0       normal         3       5.000000       76.459948       d       1.0       0.0       normal         4       5.000000       50.000000       c       0.0       0.0       normal                  394       51.492308       70.000000       a       0.0       0.0       normal         395       51.492308       70.000000       c       3.0       0.0       normal         396       51.492308       70.000000       a       0.0       0.0       normal         397       51.492308       90.000000       a       0.0       0.0       normal	0       2.000000       76.459948       c       3.0       0.0       normal abnormal abnormal         1       3.000000       76.459948       c       2.0       0.0       normal normal         2       4.000000       76.459948       d       1.0       0.0       normal normal         3       5.000000       76.459948       d       1.0       0.0       normal normal         4       5.000000       50.000000       c       0.0       0.0       normal normal                  394       51.492308       70.000000       c       0.0       2.0       normal normal         395       51.492308       70.000000       c       3.0       0.0       normal normal         397       51.492308       90.000000       a       0.0       0.0       normal normal	0       2.000000       76.459948       c       3.0       0.0       normal       abnormal       notpresent         1       3.000000       76.459948       c       2.0       0.0       normal       normal       notpresent         2       4.000000       76.459948       d       1.0       0.0       normal       normal       notpresent         3       5.000000       76.459948       d       1.0       0.0       normal       normal       notpresent         4       5.000000       50.000000       c       0.0       0.0       normal       normal       notpresent                     394       51.492308       70.000000       c       0.0       2.0       normal       normal       notpresent         396       51.492308       70.000000       c       3.0       0.0       normal       normal       notpresent         397       51.492308       90.000000       a       0.0       0.0       normal       normal       notpresent	0         2.000000         76.459948         c         3.0         0.0         normal         abnormal         notpresent         notpresent           1         3.000000         76.459948         c         2.0         0.0         normal         normal         notpresent         notpresent           2         4.000000         76.459948         d         1.0         0.0         normal         normal         notpresent         notpresent           3         5.000000         76.459948         d         1.0         0.0         normal         normal         notpresent         notpresent           4         5.000000         50.000000         c         0.0         0.0         normal         normal         notpresent         notpresent           394         51.492308         70.000000         c         0.0         0.0         normal         normal         notpresent         notpresent           395         51.492308         70.000000         c         0.0         normal         normal         notpresent         notpresent           396         51.492308         70.000000         c         3.0         0.0         normal         normal         notpresent         notpresent <t< td=""></t<>

399 rows × 25 columns

In [3]: dataset=pd.get\_dummies(dataset,drop\_first=True)
 dataset

0       2.000000       76.459948       3.0       0.0       148.112676       57.482105       3.077356       137.528754         1       3.000000       76.459948       2.0       0.0       148.112676       22.000000       0.700000       137.528754         2       4.000000       76.459948       1.0       0.0       99.000000       23.000000       0.600000       138.000000         3       5.000000       76.459948       1.0       0.0       148.112676       16.000000       0.700000       138.000000         4       5.000000       50.000000       0.0       148.112676       25.000000       0.600000       137.528754                    394       51.492308       70.000000       0.0       219.000000       36.000000       1.300000       137.528754         396       51.492308       70.000000       3.0       0.0       110.000000       115.000000       6.000000       134.000000         397       51.492308       90.000000       0.0       207.000000       80.000000       6.800000       142.000000         398       51.492308       80.0000000       0.0	Out[3]:		age	bp	al	su	bgr	bu	SC	sod
2       4.000000       76.459948       1.0       0.0       99.000000       23.000000       0.600000       138.000000         3       5.000000       76.459948       1.0       0.0       148.112676       16.000000       0.700000       138.000000         4       5.000000       50.000000       0.0       0.0       148.112676       25.000000       0.600000       137.528754                     394       51.492308       70.000000       0.0       219.000000       36.000000       1.300000       139.000000         395       51.492308       70.000000       3.0       0.0       110.000000       115.000000       6.000000       134.000000         397       51.492308       90.000000       0.0       207.000000       80.000000       6.800000       142.000000		0	2.000000	76.459948	3.0	0.0	148.112676	57.482105	3.077356	137.528754
3       5.000000       76.459948       1.0       0.0       148.112676       16.000000       0.700000       138.000000         4       5.000000       50.000000       0.0       0.0       148.112676       25.000000       0.600000       137.528754		1	3.000000	76.459948	2.0	0.0	148.112676	22.000000	0.700000	137.528754
4       5.000000       50.000000       0.0       148.112676       25.000000       0.600000       137.528754 </td <td>2</td> <td>4.000000</td> <td>76.459948</td> <td>1.0</td> <td>0.0</td> <td>99.000000</td> <td>23.000000</td> <td>0.600000</td> <td>138.000000</td>		2	4.000000	76.459948	1.0	0.0	99.000000	23.000000	0.600000	138.000000
.		3	5.000000	76.459948	1.0	0.0	148.112676	16.000000	0.700000	138.000000
394       51.492308       70.000000       0.0       219.000000       36.000000       1.300000       139.000000         395       51.492308       70.000000       0.0       2.0       220.000000       68.000000       2.800000       137.528754         396       51.492308       70.000000       3.0       0.0       110.000000       115.000000       6.000000       134.000000         397       51.492308       90.000000       0.0       207.000000       80.000000       6.800000       142.000000		4	5.000000	50.000000	0.0	0.0	148.112676	25.000000	0.600000	137.528754
395 51.492308 70.000000 0.0 2.0 220.000000 68.000000 2.800000 137.528754 396 51.492308 70.000000 3.0 0.0 110.000000 115.000000 6.000000 134.000000 397 51.492308 90.000000 0.0 0.0 207.000000 80.000000 6.800000 142.000000										
396 51.492308 70.000000 3.0 0.0 110.000000 115.000000 6.000000 134.000000 397 51.492308 90.000000 0.0 0.0 207.000000 80.000000 6.800000 142.000000		394	51.492308	70.000000	0.0	0.0	219.000000	36.000000	1.300000	139.000000
397 51.492308 90.000000 0.0 0.0 207.000000 80.000000 6.800000 142.000000		395	51.492308	70.000000	0.0	2.0	220.000000	68.000000	2.800000	137.528754
		396	51.492308	70.000000	3.0	0.0	110.000000	115.000000	6.000000	134.000000
398 51.492308 80.000000 0.0 0.0 100.000000 49.000000 1.000000 140.000000		397	51.492308	90.000000	0.0	0.0	207.000000	80.000000	6.800000	142.000000
		398	51.492308	80.000000	0.0	0.0	100.000000	49.000000	1.000000	140.000000

399 rows  $\times$  28 columns

0...+ [2].

```
Out[5]:
                                   al su
                                                  bgr
                                                              bu
                                                                                  sod
                   age
                              bp
                                                                        SC
          0
              2.000000 76.459948 3.0
                                      0.0 148.112676
                                                        57.482105 3.077356 137.528754
                                                        22.000000 0.700000 137.528754
          1
              3.000000 76.459948 2.0 0.0 148.112676
          2
              4.000000 76.459948 1.0 0.0
                                            99.000000
                                                        23.000000 0.600000 138.000000
          3
              5.000000 76.459948 1.0 0.0 148.112676
                                                        16.000000 0.700000 138.000000
          4
              5.000000 50.000000 0.0 0.0 148.112676
                                                        25.000000 0.600000 137.528754
                                  ...
        394
             51.492308 70.000000 0.0 0.0 219.000000
                                                        36.000000 1.300000 139.000000
        395 51.492308 70.000000 0.0 2.0 220.000000
                                                        68.000000 2.800000 137.528754
        396 51.492308 70.000000 3.0 0.0 110.000000
                                                      115.000000 6.000000 134.000000
        397 51.492308 90.000000 0.0 0.0 207.000000
                                                       80.000000 6.800000 142.000000
        398 51.492308 80.000000 0.0 0.0 100.000000
                                                       49.000000 1.000000 140.000000
       399 rows \times 27 columns
       dep=dataset['classification yes'].value counts()
In [6]:
        dep
Out[6]: 1
             249
             150
        Name: classification yes, dtype: int64
In [7]: dep=dataset['classification yes']
        dep
Out[7]: 0
               1
        1
               1
        2
               1
        3
               1
        4
               1
        394
               1
        395
               1
        396
               1
        397
               1
        398
        Name: classification yes, Length: 399, dtype: uint8
In [8]: from sklearn.model selection import train test split
        X_train, X_test, y_train, y_test = train_test_split(indep, dep, test size = 0.
       from sklearn.preprocessing import StandardScaler
In [9]:
        sc = StandardScaler()
        X train = sc.fit transform(X train)
        X test = sc.transform(X test)
```

```
In [10]: from sklearn.ensemble import RandomForestClassifier
         #https://scikit-learn.org/stable/modules/model evaluation.html#scoring-paramet
In [11]: from sklearn.model selection import GridSearchCV
         param grid = {'criterion':['gini','entropy'],
                       'max features': ['auto', 'sqrt', 'log2'],
                       'n estimators':[10,100]}
         grid = GridSearchCV(RandomForestClassifier(), param grid, refit = True, verbos
         # fitting the model for grid search
         grid.fit(X train , y train)
       Fitting 5 folds for each of 12 candidates, totalling 60 fits
Out[11]: GridSearchCV(estimator=RandomForestClassifier(), n jobs=-1,
                      param grid={'criterion': ['gini', 'entropy'],
                                   'max features': ['auto', 'sqrt', 'log2'],
                                   'n estimators': [10, 100]},
                      scoring='f1', verbose=3)
In [12]: # print best parameter after tuning
         #print(grid.best params )
         re=grid.cv results
         grid predictions = grid.predict(X test )
         from sklearn.metrics import confusion matrix
         cm = confusion matrix(y test, grid predictions)
         from sklearn.metrics import classification report
         clf report = classification report(y test, grid predictions)
In [13]: from sklearn.metrics import fl_score
         f1 macro=f1 score(y test,grid predictions,average='weighted')
         print("The f1 macro value for best parameter {}:".format(grid.best params ),f1
        The fl macro value for best parameter {'criterion': 'entropy', 'max features':
        'log2', 'n estimators': 10}: 0.9916844900066377
In [14]: print("The confusion Matrix:\n",cm)
       The confusion Matrix:
        [[45 0]
         [ 1 74]]
In [15]: print("The report:\n",clf report)
```

```
The report:
```

	precision	recall	f1-score	support
0 1	0.98 1.00	1.00 0.99	0.99 0.99	45 75
accuracy macro avg weighted avg	0.99 0.99	0.99 0.99	0.99 0.99 0.99	120 120 120

```
In [16]: from sklearn.metrics import roc_auc_score
    roc_auc_score(y_test,grid.predict_proba(X_test)[:,1])
```

C:\Users\user\Anaconda3\lib\site-packages\sklearn\base.py:444: UserWarning: X h
as feature names, but RandomForestClassifier was fitted without feature names
 f"X has feature names, but {self.\_\_class\_\_.\_\_name\_\_} was fitted without"

Out[16]: 0.76

In [17]: table=pd.DataFrame.from\_dict(re)

table

Out[17]:		mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criteric
	0	0.021159	0.002828	0.005167	0.001655	gi
	1	0.183381	0.032052	0.026656	0.004864	gi
	2	0.024977	0.004100	0.004559	0.000712	gi
	3	0.208134	0.010818	0.029623	0.002795	gi
	4	0.024019	0.001252	0.005918	0.000200	gi
	5	0.270043	0.015502	0.037649	0.005358	gi
	6	0.028137	0.001464	0.005966	0.000106	entrop
	7	0.315721	0.031694	0.036067	0.000687	entrop
	8	0.042569	0.001531	0.010681	0.002382	entrop
	9	0.337607	0.020517	0.038013	0.001252	entrop
	10	0.036254	0.004131	0.008329	0.000881	entrop
	11	0.297709	0.004842	0.033924	0.004193	entrop

```
In [ ]: age=float(input("Age:"))
        bP=float(input("BP:"))
        al=float(input("AL:"))
        su=float(input("SU:"))
        rbc normal=int(input("RBC NORMAL:"))
        pc normal=int(input("PC NORMAL:"))
        pcc present=float(input("PCC PREASENT:"))
        ba present=float(input("BA PRESENT:"))
        bgr=float(input("BGR:"))
        pcv=float(input("PCV:"))
        wc=float(input("WC:"))
        rc=float(input("RC:"))
        htn yes=int(input("HTN YES:"))
        dm yes=int(input("DM YES:"))
        cad yes=int(input("CAD YES:"))
        appet yes=int(input("APPET YES:"))
        pe yes=int(input("PE YES:"))
        ane_yes=int(input("ANE_YES:"))
In [ ]:
        Future Prediction=grid.predict([[age,bP,al,su,bgr,bu,sc,sod,pot,hrmo,pcv,wc,rc
        print("Future_Prediction={}".format(Future_Prediction))
In [ ]:
In [ ]:
In [ ]:
In [ ]:
```