```
In [1]: import pandas as pd
  In [2]: import numpy as np
  In [3]: from collections import Counter as c
  In [4]: import matplotlib.pyplot as plt
  In [5]: import seaborn as sns
  In [6]: import missingno as msno
  In [7]: from sklearn.metrics import accuracy_score,confusion_matrix
  In [8]: from sklearn.model_selection import train_test_split
  In [9]: from sklearn.preprocessing import LabelEncoder
 In [10]: from sklearn.linear_model import LogisticRegression
 In [11]: import pickle
 In [12]: data=pd.read_csv("F:\SEM 7\IBM Project\kidney_disease.csv")
 In [13]: data.head()
Out[13]: id age bp sg al su rbc
                                                    рсс
                                                               ba ... pcv wc rc htn dm cad appet pe ane classification
         0 0 48.0 80.0 1.020 1.0 0.0 NaN normal notpresent notpresent ... 44 7800 5.2 yes yes no good no no
         1 1 7.0 50.0 1.020 4.0 0.0 NaN normal notpresent notpresent ... 38 6000 NaN no no no good no no ckd
         2  2  62.0  80.0  1.010  2.0  3.0 normal normal notpresent notpresent ... 31  7500 NaN no yes no poor no yes
        3 3 48.0 70.0 1.005 4.0 0.0 normal abnormal present notpresent ... 32 6700 3.9 yes no no poor yes yes ckd
         4 4 51.0 80.0 1.010 2.0 0.0 normal normal notpresent notpresent ... 35 7300 4.6 no no no good no no
                                                                                                                ckd
        5 rows × 26 columns
In [14]: data.tail()
             id age bp sg al su rbc pc pcc ba ... pcv wc rc htn dm cad appet pe ane classification
         395 395 55.0 80.0 1.020 0.0 0.0 normal normal notpresent notpresent ... 47 6700 4.9 no no no good no no
         396 396 42.0 70.0 1.025 0.0 0.0 normal normal notpresent notpresent ... 54 7800 6.2 no no no good no no notckd
         397 397 12.0 80.0 1.020 0.0 0.0 normal normal notpresent notpresent ... 49 6600 5.4 no no no good no no
                                                                                                              notckd
         398 398 17.0 60.0 1.025 0.0 0.0 normal normal notpresent notpresent ... 51 7200 5.9 no no no good no no notckd
         399 399 58.0 80.0 1.025 0.0 0.0 normal normal notpresent notpresent ... 53 6800 6.1 no no no good no no
In [15]: data.head(10)
          id age bp sg al su rbc pc pc ba ... pcv wc rc htn dm cad appet pe ane
         0 0 48.0 80.0 1.020 1.0 0.0
        1 1 7.0 50.0 1.020 4.0 0.0 NaN normal notpresent notpresent ... 38 6000 NaN no no no good no no ckd
         2 2 62.0 80.0 1.010 2.0 3.0 normal normal notpresent notpresent ... 31 7500 NaN no yes no poor no yes
                                                                                                                    ckd
        3 3 48.0 70.0 1.005 4.0 0.0 normal abnormal present notpresent ... 32 6700 3.9 yes no no poor yes yes ckd
         4 4 51.0 80.0 1.010 2.0 0.0 normal normal notpresent notpresent ... 35 7300 4.6 no no no good no no
        5 5 60.0 90.0 1.015 3.0 0.0 NaN NaN notpresent notpresent ... 39 7800 4.4 yes yes no good yes no
        6 6 68.0 70.0 1.010 0.0 0.0 NaN normal notpresent notpresent ... 36 NaN NaN no no no good no no
                                                                                                                      ckd
        7 7 24.0 NaN 1.015 2.0 4.0 normal abnormal notpresent notpresent ... 44 6900 5 no yes no good yes no
        8 8 52.0 100.0 1.015 3.0 0.0 normal abnormal present notpresent ... 33 9600 4 yes yes no good no yes
                                                                                                                      ckd
        9 9 53.0 90.0 1.020 2.0 0.0 abnormal abnormal present notpresent ... 29 12100 3.7 yes yes no poor no yes
        10 rows × 26 columns
In [16]: data.drop(["id"],axis=1,inplace=True)
In [17]: data.head(10)
Out[17]: age bp sg al su
                                                     pcc
                                             pc
                                                               ba bgr ... pcv wc rc htn dm cad appet pe ane classification
                                    NaN normal notpresent notpresent 121.0 ... 44 7800 5.2 yes yes no good no no
        0 48.0 80.0 1.020 1.0 0.0
        1 7.0 50.0 1.020 4.0 0.0 NaN normal notpresent notpresent NaN ... 38 6000 NaN no no no good no no
        2 62.0 80.0 1.010 2.0 3.0 normal notpresent notpresent 423.0 ... 31 7500 NaN no yes no poor no yes
        3 48.0 70.0 1.005 4.0 0.0 normal abnormal present notpresent 117.0 ... 32 6700 3.9 yes no no poor yes yes
                                                                                                                        ckd
         4 51.0 80.0 1.010 2.0 0.0
                                  normal normal notpresent notpresent 106.0 ... 35 7300 4.6 no no no good no no
        5 60.0 90.0 1.015 3.0 0.0 NaN NaN notpresent notpresent 74.0 ... 39 7800 4.4 yes yes no good yes no
                                                                                                                        ckd
         6 68.0 70.0 1.010 0.0 0.0
                                 NaN normal notpresent notpresent 100.0 ... 36 NaN NaN no no no good no no
                                                                                                                      ckd
        7 24.0 NaN 1.015 2.0 4.0 normal abnormal notpresent notpresent 410.0 ... 44 6900 5 no yes no good yes no
         8 52.0 100.0 1.015 3.0 0.0 normal abnormal present notpresent 138.0 ... 33 9600
                                                                                      4 yes yes no good no yes
                                                                                                                         ckd
        9 53.0 90.0 1.020 2.0 0.0 abnormal abnormal present notpresent 70.0 ... 29 12100 3.7 yes yes no poor no yes ckd
```

10 rows × 25 columns

```
In [18]: data.columns
In [19]: data.columns=['age','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','specific_gravity','albumin','sugar','red_blood_cells','pus_cell','pus_cell_clumps','bacteria','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','blood_pressure','b
In [20]: data.columns
In [21]: data.columns
In [22]: data.info()
                              RangeIndex: 400 entries, 0 to 399
Data columns (total 25 columns):
# Column Non-Null Count Dtype
                                                                                                                         391 non-null
388 non-null
                                                                                                                                                                        float64
float64
                                               age
blood_pressure
                                               specific_gravity albumin
                                                                                                                         353 non-null
354 non-null
                                                                                                                                                                        float64
float64
                                               sugar
red_blood_cells
                                                                                                                         351 non-null
248 non-null
                                                                                                                                                                        float64
                                               sugar
red_blood_cells
pus_cell
pus_cell_clumps
                                                                                                                       248 non-null
335 non-null
396 non-null
396 non-null
356 non-null
351 non-null
381 non-null
313 non-null
312 non-null
348 non-null
350 non-null
295 non-null
270 non-null
                                                                                                                                                                        object
                                                                                                                                                                        object
object
                                                                                                                                                                       object
object
float64
float64
float64
float64
float64
object
object
object
                                           bacteria blood glucose random blood urea blood urea serum creatinine sodium potassium hemoglobin packed_cell_volume white_blood_cell_count red_blood_cell_count hypertension diabetesmellitus coronary_artery_disease
                                               bacteria
                                                                                                                         398 non-null
398 non-null
                                                                                                                                                                        object
                                             coronary_artery_disease 398 non-null appetite 399 non-null 399 non-null
                                                                                                                                                                        object
                                                                                                                                                                        object
object
                                   21
                                             pedal_edema
anemia
                                                                                                                         399 non-null
399 non-null
                                                                                                                                                                        object
                                                                                                                                                                         object
                                             class
                                                                                                                         400 non-null
                                                                                                                                                                        object
                               dtypes: float64(11), object(14)
memory usage: 78.2+ KB
    In [23]: data['class'].unique()
    Out[23]: array(['ckd', 'ckd\t', 'notckd'], dtype=object)
    In [24]:
                                  data['class']=data['class'].replace("ckd\t","ckd")
data['class'].unique()
    Out[24]: array(['ckd', 'notckd'], dtype=object)
                                  catcols=set(data.dtypes[data.dtypes=='0'].index.values)
                                  print(catcols)
                                 {'anemia', 'appetite', 'pus_cell_clumps', 'packed_cell_volume', 'red_blood_cell_count', 'class', 'bacteria', 'hypertension', 'pus_cell', 'pedal_edema', 'red_blood_cells', 'coronary_artery_disease', 'white_blood_cell_count', 'diabetesmellitus')
    In [26]:
    for i in catcols:
        print("Columns:",i)
        print(c(data[i]))
        print('*'*120*'\n')
                                Columns: anemia
Counter({'no': 339, 'yes': 60, nan: 1})
                                 Counter({'good': 317, 'poor': 82, nan: 1})
                                Columns: pus_cell_clumps
Counter({'notpresent': 354, 'present': 42, nan: 4})
                               Columns: packed_cell_volume

Counter((nan: 70, '52': 21, '41': 21, '44': 19, '48': 19, '40': 16, '43': 14, '45': 13, '42': 13, '32': 12, '36': 12, '33': 12, '28': 12, '59': 12, '37': 11, '34': 11, '35': 9, '29': 9, '30': 9, '46': 9, '31': 8, '39': 7, '24': 7, '26': 6, '38': 5, '47': 4, '49': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55': 4, '55'
                               Columns: red_blood_cell_count

Counter((nan: 138, '5.2': 18, '4.5': 16, '4.9': 14, '4.7': 11, '3.9': 18, '5': 18, '4.8': 18, '4.6': 9, '3.4': 9, '3.7': 8, '6.1': 8, '5

5:: 8, '5.9': 8, '3.8': 7, '5.4': 7, '5.8': 7, '5.3': 7, '4': 6, '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, '6.3': 4, '3.5': 3, '3.3': 3, '3': 3, '2.6': 2, '2.8': 2, '2.5': 2, '3.1': 2, '2.1': 2, '2.9': 2, '2.3': 1, '8': 1, '2.4': 1, '\tr': 1)
                                 Columns: class
Counter({'ckd': 250, 'notckd': 150})
                                 Counter({'notpresent': 374, 'present': 22, nan: 4})
                                Columns: hypertension
```

```
Columns: bacteria
                                   Counter({'notpresent': 374, 'present': 22, nan: 4})
                                    Counter({'no': 251, 'yes': 147, nan: 2})
                                   Columns: pus_cell
Counter(('normal': 259, 'abnormal': 76, nan: 65})
                                   Counter({'no': 323, 'yes': 76, nan: 1})
                                   Counter({'normal': 201, nan: 152, 'abnormal': 47})
                                  Columns: coronary_artery_disease
Counter(('no': 362, 'yes': 34, '\tno': 2, nan: 2})
                                 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, '12000': 6, '12000': 6, '7500': 5, '8300': 5, '7900': 5, '8600': 5, '5600': 5, '8200': 5, '8200': 5, '8200': 5, '8200': 4, '7500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 4, '1500': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 2, '12100': 1, '12200': 2, '12100': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200': 1, '1200':
                                   Columns: diabetesmellitus
Counter(('no': 258, 'yes': 134, '\tno': 3, '\tyes': 2, nan: 2, ' yes': 1})
                                    catcols.remove('red_blood_cell_count')
catcols.remove('packed_cell_volume')
                                     catcols.remove('white blood cell count')
                                          print(catcols)
                                       {'anemia', 'appetite', 'pus_cell_clumps', 'class', 'bacteria', 'hypertension', 'pus_cell', 'pedal_edema', 'red_blood_cells', 'coronary_ar
                                        tery disease', 'diabetesmellitus'
  In [28]: contcols=set(data.dtypes[data.dtypes!='0'].index.values)
                                       {'albumin', 'sugar', 'serum_creatinine', 'blood glucose random', 'potassium', 'sodium', 'blood_pressure', 'blood_urea', 'hemoglobin', 'specific_gravity', 'age'}
In [29]: for i in contcols:
    print("Columns:",i)
    print(c(data[i]))
    print('*'*128+'\n')
                                       Columns: albumin
Counter((0.0: 199, 1.0: 44, 2.0: 43, 3.0: 43, 4.0: 24, nan: 1, nan: 1
                                       n: 1, nan: 1, nan: 1})
                                      Columns: sugar

Counter({0.0: 290, 2.0: 18, 3.0: 14, 4.0: 13, 1.0: 13, 5.0: 3, nan: 1, nan: 1,
                                     Columns: serum_creatinine
Counter((1.2: 40, 1.1: 24, 1.0: 23, 0.5: 23, 0.7: 22, 0.9: 22, 0.6: 18, 0.8: 17, 2.2: 10, 1.5: 9, 1.7: 9, 1.3: 8, 1.6: 8, 1.8: 7, 1.4: 7, 2.5: 7, 2.8: 7, 1.9: 6, 2.7: 5, 2.1: 5, 2.0: 5, 3.2: 5, 3.3: 5, 3.9: 4, 7.3: 4, 4.0: 3, 2.4: 3, 3.4: 3, 2.9: 3, 5.3: 3, 2.3: 3, 7.2: 2, 4.6: 2, 4.1: 2, 5.2: 2, 6.3: 2, 3.0: 2, 6.1: 2, 6.7: 2, 5.6: 2, 6.5: 2, 4.4: 2, 6.0: 2, 3.8: 1, 24.0: 1, 9.6: 1, 7.6: 1, 7.7: 1, nan: 1, 10.8: 1, 5.9: 1, 3.25: 1, nan: 1, 9.7: 1, 6.4: 1, 32.0: 1, nan: 1, nan: 1, 8.5: 1, 15.0: 1, 3.6: 1, 10.2: 1, 11.5: 1, nan: 1, 12.2: 1, 9. 2: 1, 13.8: 1, 16.9: 1, 7.1: 1, 18.0: 1, 13.0: 1, 48.1: 1, 14.2: 1, 16.4: 1, nan: 1, nan: 1, 2.6: 1, 7.5: 1, 4.3: 1, 18.1: 1, 11.8: 1, 9. 3: 1, 6.8: 1, 13.5: 1, nan: 1, 12.8: 1, 11.9: 1, nan: 1, nan: 1, nan: 1, 13.4: 1, 15.2: 1, 13.3: 1, nan: 1, nan: 1, nan: 1, nan: 1, 0.4: 1})
```

Columns: blood glucose random

Columns: blood glucose random
Counter(90:0:18, 100:0:19, 50:0:19, 107:0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18, 117.0:18,

Columns: potassium

Counter((5.0: 30, 3.5: 30, 4.9: 27, 4.7: 17, 4.8: 16, 4.0: 14, 4.2: 14, 4.1: 14, 3.8: 14, 3.9: 14, 4.4: 14, 4.5: 13, 3.7: 12, 4.3: 12, 3.6: 8, 4.6: 7, 3.4: 5, 5.2: 5, 5.7

4, 5.3: 4, 3.2: 3, 5.5: 3, 2.0: 3, 5.4: 3, 6.3: 3, 3.3: 3, 2.5: 2, 5.8: 2, 5.9: 2, 5.6: 2, 3.0: 2, 6.5: 2, nan: 1, nan

Columns: sodium

Counter([35.6: 40, 140.6: 25, 141.6: 22, 139.6: 21, 142.6: 20, 138.6: 20, 137.6: 19, 136.6: 17, 150.6: 17, 147.6: 13, 145.6: 11, 132.6: 10, 146.6: 10, 131.6: 9, 144.6: 9, 133.6: 8, 130.6: 7, 134.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6, 143.6: 6

Counter({80.0: 116, 70.0: 112, 60.0: 71, 90.0: 53, 100.0: 25, 50.0: 5, 110.0: 3, nan: 1, nan: 1, 140.0: 1, 180.0: 1, nan: 1)

Columns: blood_urea

Counter(46.8: 15, 25.0: 13, 19.0: 11, 40.0: 10, 18.0: 9, 50.0: 9, 15.0: 9, 48.0: 9, 26.0: 8, 27.0: 8, 32.0: 8, 49.0: 8, 36.0: 7, 28.0: 7, 20.0: 7, 70.0: 7, 30.0: 7, 30.0: 7, 30.0: 7, 30.0: 7, 30.0: 7, 30.0: 5, 35.0: 5, 35.0: 5, 35.0: 5, 35.0: 5, 42.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0: 8, 51.0:

0: 1, 223.0: 1, 98.6: 1, 158.0: 1, 94.0: 1, 74.0: 1, nan: 1, 150.0: 1, nan: 1, 61.0: 1, 57.0: 1, nan: 1, 95.0: 1, 191.0: 1, nan: 1, 93.0: 1, 241.0: 1, 64.0: 1, 79.0: 1, 21 5.0: 1, 309.0: 1, nan: 1, nan: 1, nan: 1, nan: 1, nan: 1, nan: 1})

Counter({15.0: 16, 10.9: 8, 9.8: 7, 11.1: 7, 13.0: 7, 13.6: 7, 11.3: 6, 10.3: 6, 12.0: 6, 13.9: 6, 15.4: 5, 11.2: 5, 10.8: 5, 9.7: 5, 12.6: 5, 7.9: 5, 10.0: 5, 14.0: 5, 14. Courter({15.0: 16, 16.9: 8, 9.8: 7, 11.1: 7, 13.0: 7, 13.0: 7, 13.0: 7, 11.3: 6, 12.0: 6, 13.9: 6, 13.4: 5, 14.2: 5, 14.2: 5, 12.2: 4, 12.4: 4, 12.2: 4, 15.2: 4, 91.4: 4, 11.2: 4, 13.5: 4, 4, 15.2: 4, 13.1: 4, 13.2: 4, 13.8: 4, 13.7: 4, 13.4: 4, 17.0: 4, 15.5: 4, 15.2: 4, 91.6: 3, 16.5: 3, 9.5: 3, 9.4: 3, 12.7: 3, 9.9: 3, 10.1: 3, 8.6: 3, 11.0: 3, 15.6: 3, 8.1: 3, 8.3: 3, 10.4: 3, 11.8: 3, 11.4: 3, 11.5: 3, 15.9: 3, 14.5: 3, 16.2: 3, 14.4: 3, 14.4: 3, 14.2: 3, 16.3: 3, 16.5: 3, 15.7: 3, 16.4: 3, 14.9: 3, 15.3: 3, 17.8: 3, 12.1: 2, 93: 2, 10.2: 2, 10.5: 2, 60: 2, 11.7: 2, 80: 2, 12.3: 2, 87: 2, 15.3: 2, 14.4: 2, 15.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2: 4, 16.2:

Columns: specific_gravity

Counter((1.02 106) 1.01 84, 1.025: 81, 1.015: 75, 1.005: 7, nan: 1, na

Columns: age
Columns: (60.0: 19, 65.0: 17, 48.0: 12, 50.0: 12, 55.0: 12, 47.0: 11, 62.0: 10, 45.0: 10, 54.0: 10, 59.0: 10, 56.0: 10, 61.0: 9, 70.0: 9, 46.0: 9, 34.0: 9, 68.0: 8, 73.0: 8, 64.0: 8, 71.0: 8, 57.0: 8, 63.0: 7, 72.0: 7, 67.0: 7, 30.0: 7, 42.0: 6, 69.0: 6, 35.0: 6, 44.0: 6, 43.0: 6, 33.0: 6, 51.0: 5, 52.0: 5, 53.0: 5, 75.0: 5, 76.0: 5, 58.0: 5, 4
1.0: 5, 66.0: 5, 24.0: 4, 40.0: 4, 39.0: 4, 80.0: 4, 22.0: 4, 74.0: 3, 30.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0: 1, 10.0

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

{'serum_creatinine', 'blood glucose random', 'potassium', 'sodium', 'blood_pressure', 'blood_urea', 'hemoglobin', 'age'}

```
[31]:
              contcols.add('red_blood_cell_count')
contcols.add('packed_cell_volume')
contcols.add('white_blood_cell_count')
               print(contcols)
```

{"serum creatinine", "blood glucose random", "red blood cell count", "potassium", "packed cell volume", "white blood cell count", "sodium", "blood pressure", "blood urea", hemoglobin', 'age'

```
In [32]:
    catcols.add('specific_gravity')
    catcols.add('albumin')
    catcols.add('sugar')
    print(catcols)
                                              {'albumin', 'sugar', 'anemia', 'appetite', 'pus_cell_clumps', 'class', 'bacteria', 'hypertension', 'pus_cell', 'pedal_edema', 'red_blood_cells', 'coronary_artery_disease', 'specific_gravity', 'diabetesmellitus'}
  In [33]: data['coronary_artery_disease']-data.coronary_artery_disease.replace('\tro','no') c(data['coronary_artery_disease'])
     Out[33]: Counter({'no': 364, 'yes': 34, nan: 2})
  In [34]: data['diabetesmellitus']=data.diabetesmellitus.replace(to_replace=('\tno':'no','\tyes':'yes',' yes':'yes',' no':'no')) c(data['diabetesmellitus'])
     Out[34]: Counter({'yes': 137, 'no': 261, nan: 2})
     In [35]: data.isnull().any()
data.isuali().any()

age True

specific_gravity
slbustn True
specific_gravity
specific_gravity
specific_gravity
specific_gravity
specific_gravity
specific_gravity
specific_gravity
specific_specific_gravity
specific_specific_gravity
specific_gravity
specific_specific_gravity
specific_gravity
spe
                                                    class
dtype: int64
        In [37]:

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')
                                                    data['blood glucose random'].fillna(data['blood glucose random'].mean(),inplace=True)
data['blood_pressure'].fillna(data['blood_pressure'].mean(),inplace=True)
data['blood_unea'].fillna(data['blood_pressure'].mean(),inplace=True)
data['rhemoglobin'].fillna(data['rhemoglobin'].mean(),inplace=True)
data['rhemoglobin'].fillna(data['rhemoglobin'].mean(),inplace=True)
data['rotassium'].fillna(data['rpotassium'].mean(),inplace=True)
data['rotassium'].fillna(data['rotassium'].mean(),inplace=True)
data['resrum_creatinine'].fillna(data['sorum_creatinine'].mean(),inplace=True)
data['sorum_creatinine'].fillna(data['sorum_creatinine'].mean(),inplace=True)
data['white_blood_cell_count'].fillna(data['white_blood_cell_count'].mean(),inplace=True)
                                                     data['age'].fillna(data['age'].mode()[0],inplace=True)
data['hypertension'].fillna(data['hypertension'].mode()[0],inplace=True)
data['hypertension'].fillna(data['hypertension'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['hyde,lood_calie'].fillna(data['red_blood_calie'].mode()[0],inplace=True)
data['red_blood_calie'].fillna(data['appetite'].mode()[0],inplace=True)
data['bacteria'].fillna(data['appetite'].mode()[0],inplace=True)
data['bacteria'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['diabetesmellitus'].fillna(data['appetite'].mode()[0],inplace=True)
data['diabetesmellitus'].fillna(data['appetite'].mode()[0],inplace=True)
data['paca[_dema'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
        In [40]: from sklearn.preprocessing import LabelEnco
     In [41]:
    for i in catcols:
        print("LaseL ENCODING OF:",i)
        LEi=LabelEncoder()
        print(c(data[i]))
        data[i]=LEi.fit_transform(data[i])
        print(c(data[i]))
        print(c(data[i]))
        print(c(data[i]))
                                              LABEL ENCODING OF: albumin

Counter((e.e: 245, 1:44, 2.0: 43, 3.0: 43, 4.0: 24, 5.0: 1))

Counter((e. 245, 1:44, 2.43, 3: 45, 4: 24, 5: 1))

LABEL ENCODING OF: sugar

Counter((0.0: 339, 2.0: 18, 3.0: 14, 4.0: 13, 1.0: 13, 5.0: 3))

Counter((e: 339, 2: 18, 3: 14, 4: 13, 1: 13, 5: 3))
                                                LABEL ENCODING OF: anemia
Counter({'no': 340, 'yes': 60})
Counter({0: 340, 1: 60})
                                              LABEL ENCOUNS OF: appetite
Counter({ good : 318, 'poor': 82})
Counter({0: 318, 1: 82})

LABEL ENCOUNS OF: pus_cell_clumps
Counter({0: 358, 1: 42})

Counter({0: 358, 1: 42})
                                                LABEL ENCODING OF: class
Counter({'ckd': 250, 'notckd': 150})
Counter({0: 250, 1: 150})
                                                 Counter({0: 578, 1: 22})
                                                LABEL ENCODING OF: hypertension
Counter({'no': 253, 'yes': 147})
Counter({0: 253, 1: 147})
                                                LABEL ENCODING OF: pus_cell
Counter({'normal': 324, 'abnormal': 76})
Counter({1: 324, 0: 76})
                                                LABEL ENCODING OF: pedal_edema
Counter({'no': 324, 'yes': 76})
Counter({0: 324, 1: 76})
                                                LABEL ENCODING OF: red_blood_cells
Counter(('normal': 353, 'abnormal': 47})
Counter((1: 353, 0: 47})
                                                LABEL ENCODING OF: coronary_artery_disease
Counter(('no': 366, 'yes': 34})
Counter((0: 366, 1: 34})
```

```
LABEL ENCODING OF: specific gravity
Counter({3.02: 153, 1.01: 84, 1.025: 81, 1.015: 75, 1.005: 7})
Counter({5: 153, 1: 84, 4: 81, 2: 75, 0: 7})

LABEL ENCODING OF: diabetesmellitus
Counter({0: 263, 'yes': 137})
Counter({0: 263, 'yes': 137})
  In [42]: selcols=['red_blood_cells','pus_cell','blood_glucose random','blood_urea','pedal_edema','anemia','diabetesmellitus','coronary_artery_disease']
 (400, 8)
(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(x_test.shape)
print(x_test.shape)
              (320, 8)
(320, 1)
(80, 8)
(80, 1)
 In [45]:
               from sklearn.ensemble import RandomForestClassifier
lgr = RandomForestClassifier()
 In [46]: #from sklearn.linear_model import LogisticRegression
 In [47]: #lgr=LogisticRegression(solver='lbfgs', max_iter=1000) lgr.fit(x_train.values, y_train.values.ravel())
Out[47]: RandomForestClassifier()
In [47]: #Lgr=LogisticRegression(solver='lbfgs', max_iter=1000)
lgr.fit(x_train.values, y_train.values.ravel())
In [48]: y_pred=lgr.predict(x_test.values)
[0]
Out[49]: Counter({0: 1})
In [50]: accuracy_score(y_test,y_pred)
out[50]: 0.95
In [51]: conf_mat=confusion_matrix(y_test,y_pred)
conf_mat
Out[51]: array([[52, 2], [2, 24]], dtype=int64)
In [52]: pickle.dump(lgr,open('CKD.pkl','wb'))
```