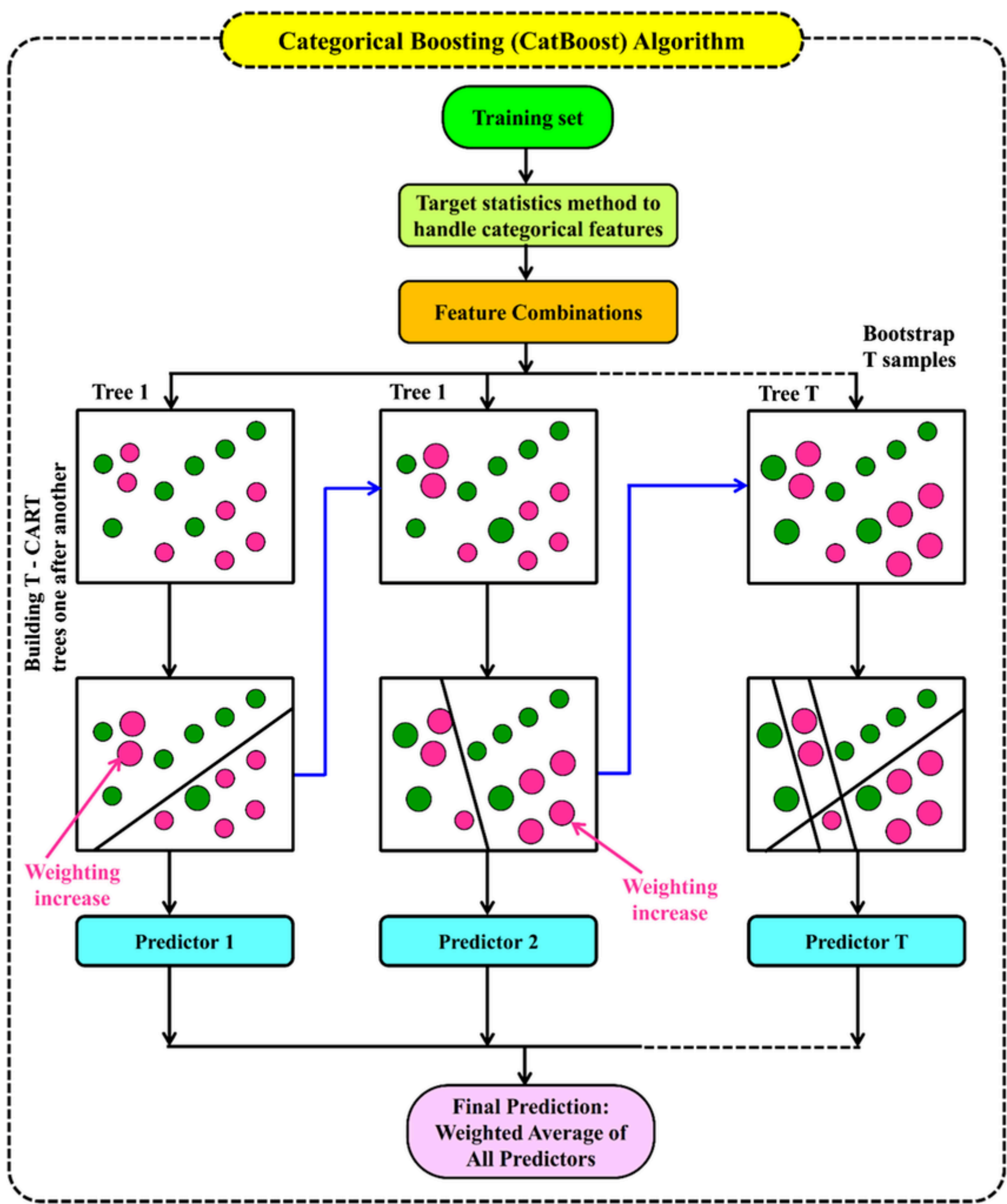


CatBoost



- CatBoost (Categorical Boosting) is a cutting-edge boosting algorithm that addresses the challenges associated with categorical features in machine learning models.
- XGBoost has established itself as a dominant force in the world of boosting algorithms, but there's another contender worthy of your attention: CatBoost.
- This powerful algorithm leverages gradient boosting techniques to deliver exceptional performance, particularly when dealing with categorical data.
- CatBoost shines in its ability to handle categorical features efficiently. Unlike traditional approaches that require converting categories to numerical values, CatBoost uses a unique encoding method that preserves the inherent structure within categorical data.
- This not only simplifies the pre-processing stage but can also lead to better model performance.
- **Key Advantages of CatBoost:**
 - **Speed and Efficiency:** CatBoost boasts impressive training speeds, making it ideal for large datasets. The efficient handling of categorical features further contributes to its computational advantage.
 - **State-of-the-Art Accuracy:** CatBoost consistently delivers competitive results on various tasks, often rivaling the performance of XGBoost.
 - **Automatic Feature Selection:** CatBoost incorporates automatic feature selection, reducing the need for extensive manual feature engineering and saving valuable time.
 - **Robustness to Outliers:** The algorithm exhibits strong resilience to outliers in the data, leading to more stable and generalizable models.
- **Considerations for CatBoost:**
 - **Relative Newcomer:** Compared to XGBoost, CatBoost is a relatively newer algorithm. While it shows great promise, it may have a slightly smaller user base and fewer community resources available.
 - **Hyperparameter Tuning:** While CatBoost offers default settings that often work well, achieving optimal performance might still require some experimentation with hyperparameters.
- CatBoost offers a compelling alternative to established boosting algorithms like XGBoost.
- Its exceptional speed, efficient handling of categorical data, and competitive accuracy make it a valuable tool for your data science arsenal.
- As CatBoost continues to mature, it's likely to become an even more prominent player in the boosting landscape.

In [1]: `### Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.figure_factory as ff
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from sklearn.metrics import mean_squared_error, r2_score
import warnings
warnings.filterwarnings('ignore')`

In [2]: `### Import the Dataset
df = pd.read_csv(r'C:\Users\hp\Desktop\100DaysOfDataScience\Day 53\kidney_disease.csv',header=0)
df.head()`

Out[2]:

	id	age	bp	sg	al	su	rbc	pc	pcc	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	ckd
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	ckd

5 rows × 26 columns

In [3]: `df.shape ### Checking Shape`

Out[3]: (400, 26)

In [4]: `df.describe() ### Get information of the Dataset`

Out[4]:

	id	age	bp	sg	al	su	bgr	bu	sc	sod	pot	hemo
count	400.000000	391.000000	388.000000	353.000000	354.000000	351.000000	356.000000	381.000000	383.000000	313.000000	312.000000	348.000000
mean	199.500000	51.483376	76.469072	1.017408	1.016949	0.450142	148.036517	57.425722	3.072454	137.528754	4.627244	12.526437
std	115.614301	17.169714	13.683637	0.005717	1.352679	1.099191	79.281714	50.503006	5.741126	10.408752	3.193904	2.912587
min	0.000000	2.000000	50.000000	1.005000	0.000000	0.000000	22.000000	1.500000	0.400000	4.500000	2.500000	3.100000
25%	99.750000	42.000000	70.000000	1.010000	0.000000	0.000000	99.000000	27.000000	0.900000	135.000000	3.800000	10.300000
50%	199.500000	55.000000	80.000000	1.020000	0.000000	0.000000	121.000000	42.000000	1.300000	138.000000	4.400000	12.650000
75%	299.250000	64.500000	80.000000	1.020000	2.000000	0.000000	163.000000	66.000000	2.800000	142.000000	4.900000	15.000000
max	399.000000	90.000000	180.000000	1.025000	5.000000	5.000000	490.000000	391.000000	76.000000	163.000000	47.000000	17.800000

In [5]: `df.columns ### Checking Columns`

Out[5]: Index(['id', 'age', 'bp', 'sg', 'al', 'su', 'rbc', 'pc', 'pcc', 'ba', 'bgr', 'bu', 'sc', 'sod', 'pot', 'hemo', 'pcv', 'wc', 'rc', 'htn', 'dm', 'cad', 'appet', 'pe', 'ane', 'classification'], dtype='object')

In [6]: `df.info() ### Checking Information About a DataFrame`

```
<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.isnull().sum() ### Checking Null Values in the Data`

Out[7]:

id	0
age	9
bp	12
sg	47
al	46
su	49
rbc	152
pc	65
pcc	4
ba	4
bgr	44
bu	19
sc	17
sod	87
pot	88
hemo	52
pcv	70
wc	105
rc	130
htn	2
dm	2
cad	2
appet	1
pe	1
ane	1
classification	0

dtype: int64

In [8]: df1 = pd.DataFrame.copy(df)
df1.shape

Out[8]: (400, 26)

In [9]: *### Dropping id column*
df1.drop('id', axis = 1, inplace = True)

In [10]: *### Renaming columns*
df1.columns = ['age', 'blood_pressure', 'specific_gravity', 'albumin', 'sugar', 'red_blood_cells', 'pus_cell',
 'pus_cell_clumps', 'bacteria', 'blood_glucose_random', 'blood_urea', 'serum_creatinine', 'sodium',
 'potassium', 'haemoglobin', 'packed_cell_volume', 'white_blood_cell_count', 'red_blood_cell_count',
 'hypertension', 'diabetes_mellitus', 'coronary_artery_disease', 'appetite', 'peda_edema',
 'aanemia', 'class']

df1.head()

Out[10]:

	age	blood_pressure	specific_gravity	albumin	sugar	red_blood_cells	pus_cell	pus_cell_clumps	bacteria	blood_glucose_random	...	packed_cell_volume	white_blood_cell_count	red_blood_cell_count	hypertension
0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	121.0	...	44	7800	5.2	yes
1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	NaN	...	38	6000	NaN	no
2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	423.0	...	31	7500	NaN	no
3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	117.0	...	32	6700	3.9	yes
4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	106.0	...	35	7300	4.6	no

5 rows × 25 columns

In [11]: *### Dropping diabetes_mellitus column*
df1.drop('diabetes_mellitus', axis = 1, inplace = True)

```
In [12]: for i in df1.columns:
        print({i:df1[i].unique()}) ### Checking Unique values in each columns

{'age': array([48., 7., 62., 51., 60., 68., 24., 52., 53., 50., 63., 40., 47.,
        61., 21., 42., 75., 69., nan, 73., 70., 65., 76., 72., 82., 46.,
        45., 35., 54., 11., 59., 67., 15., 55., 44., 26., 64., 56., 5.,
        74., 38., 58., 71., 34., 17., 12., 43., 41., 57., 8., 39., 66.,
        81., 14., 27., 83., 30., 4., 3., 6., 32., 80., 49., 90., 78.,
        19., 2., 33., 36., 37., 23., 25., 20., 29., 28., 22., 79.])}
{'blood_pressure': array([ 80., 50., 70., 90., nan, 100., 60., 110., 140., 180., 120.])}
{'specific_gravity': array([1.02, 1.01, 1.005, 1.015, nan, 1.025])}
{'albumin': array([ 1., 4., 2., 3., 0., nan, 5.])}
{'sugar': array([ 0., 3., 4., 1., nan, 2., 5.])}
{'red_blood_cells': array([nan, 'normal', 'abnormal'], dtype=object)}
{'pus_cell': array(['normal', 'abnormal', nan], dtype=object)}
{'pus_cell_clumps': array(['notpresent', 'present', nan], dtype=object)}
{'bacteria': array(['notpresent', 'present', nan], dtype=object)}
{'blood_glucose_random': array([121., nan, 423., 117., 106., 74., 100., 410., 138., 70., 490.,
        380., 208., 98., 157., 76., 99., 114., 263., 173., 95., 108.,
        156., 264., 123., 93., 107., 159., 140., 171., 270., 92., 137.,
        204., 79., 207., 124., 144., 91., 162., 246., 253., 141., 182.,
        86., 150., 146., 425., 112., 250., 360., 163., 129., 133., 102.,
        158., 165., 132., 104., 127., 415., 169., 251., 109., 280., 210.,
        219., 295., 94., 172., 101., 298., 153., 88., 226., 143., 115.,
        89., 297., 233., 294., 323., 125., 90., 308., 118., 224., 128.,
        122., 214., 213., 268., 256., 84., 105., 288., 139., 78., 273.,
        242., 424., 303., 148., 160., 192., 307., 220., 447., 309., 22.,
        111., 261., 215., 234., 131., 352., 80., 239., 110., 130., 184.,
        252., 113., 230., 341., 255., 103., 238., 248., 120., 241., 269.,
        201., 203., 463., 176., 82., 119., 97., 96., 81., 116., 134.,
        85., 83., 87., 75.])}
{'blood_urea': array([ 36., 18., 53., 56., 26., 25., 54., 31., 60.,
        107., 55., 72., 86., 90., 162., 46., 27.,
        148., 180., 163., nan, 50., 75., 45., 28., 155.,
        33., 39., 153., 29., 65., 103., 70., 80., 20.,
        202., 77., 89., 24., 17., 32., 114., 66., 38.,
        164., 142., 96., 391., 15., 111., 73., 19., 92.,
        35., 16., 139., 48., 85., 98., 186., 37., 47.,
        52., 82., 51., 106., 22., 217., 88., 118., 50.1,
        71., 34., 40., 21., 219., 30., 125., 166., 49.,
        208., 176., 68., 145., 165., 322., 23., 235., 132.,
        76., 42., 44., 41., 113., 1.5, 146., 58., 133.,
        137., 67., 115., 223., 98.6, 158., 94., 74., 150.,
        61., 57., 95., 191., 93., 241., 64., 79., 215.,
        309., 10.])}
{'serum_creatinine': array([ 1.2, 0.8, 1.8, 3.8, 1.4, 1.1, 24., 1.9, 7.2,
        4., 2.7, 2.1, 4.6, 4.1, 9.6, 2.2, 5.2, 1.3,
        1.6, 3.9, 76., 7.7, nan, 2.4, 7.3, 1.5, 2.5,
        2., 3.4, 0.7, 1., 10.8, 6.3, 5.9, 0.9, 3.,
        3.25, 9.7, 6.4, 3.2, 32., 0.6, 6.1, 3.3, 6.7,
        8.5, 2.8, 15., 2.9, 1.7, 3.6, 5.6, 6.5, 4.4,
        10.2, 11.5, 0.5, 12.2, 5.3, 9.2, 13.8, 16.9, 6.,
        7.1, 18., 2.3, 13., 48.1, 14.2, 16.4, 2.6, 7.5,
        4.3, 18.1, 11.8, 9.3, 6.8, 13.5, 12.8, 11.9, 12.,
        13.4, 15.2, 13.3, 0.4])}
{'sodium': array([ nan, 111., 142., 104., 114., 131., 138., 135., 130.,
        141., 139., 4.5, 136., 129., 140., 132., 133., 134.,
        125., 163., 137., 128., 143., 127., 146., 126., 122.,
        147., 124., 115., 145., 113., 120., 150., 144.])}
{'potassium': array([ nan, 2.5, 3.2, 4., 3.7, 4.2, 5.8, 3.4, 6.4, 4.9, 4.1,
        4.3, 5.2, 3.8, 4.6, 3.9, 4.7, 5.9, 4.8, 4.4, 6.6, 39.,
        5.5, 5., 3.5, 3.6, 7.6, 2.9, 4.5, 5.7, 5.4, 5.3, 47.,
        6.3, 5.1, 5.6, 3., 2.8, 2.7, 6.5, 3.3])}
{'haemoglobin': array([15.4, 11.3, 9.6, 11.2, 11.6, 12.2, 12.4, 10.8, 9.5, 9.4, 9.7,
        9.8, 5.6, 7.6, 12.6, 12.1, 12.7, 10.3, 7.7, 10.9, nan, 11.1,
        9.9, 12.5, 12.9, 10.1, 12., 13., 7.9, 9.3, 15., 10., 8.6,
        13.6, 10.2, 10.5, 6.6, 11., 7.5, 15.6, 15.2, 4.8, 9.1, 8.1,
        11.9, 13.5, 8.3, 7.1, 16.1, 10.4, 9.2, 6.2, 13.9, 14.1, 6.,
        11.8, 11.7, 11.4, 14., 8.2, 13.2, 6.1, 8., 12.3, 8.4, 14.3,
        9., 8.7, 10.6, 13.1, 10.7, 5.5, 5.8, 6.8, 8.8, 8.5, 13.8,
        11.5, 7.3, 13.7, 12.8, 13.4, 6.3, 3.1, 17., 15.9, 14.5, 15.5,
        16.2, 14.4, 14.2, 16.3, 14.8, 16.5, 15.7, 13.3, 14.6, 16.4, 16.9,
        16., 14.7, 16.6, 14.9, 16.7, 16.8, 15.8, 15.1, 17.1, 17.2, 15.3,
        17.3, 17.4, 17.7, 17.8, 17.5, 17.6])}
{'packed_cell_volume': array(['44', '38', '31', '32', '35', '39', '36', '33', '29', '28', nan,
        '16', '24', '37', '30', '34', '40', '45', '27', '48', '\t?', '52',
        '14', '22', '18', '42', '17', '46', '23', '19', '25', '41', '26',
        '15', '21', '43', '20', '\t43', '47', '9', '49', '50', '53', '51',
        '54'], dtype=object)}
{'white_blood_cell_count': array(['7800', '6000', '7500', '6700', '7300', nan, '6900', '9600',
        '12100', '4500', '12200', '11000', '3800', '11400', '5300', '9200',
        '6200', '8300', '8400', '10300', '9800', '9100', '7900', '6400',
        '8600', '18900', '21600', '4300', '8500', '11300', '7200', '7700',
        '14600', '6300', '\t6200', '7100', '11800', '9400', '5500', '5800',
        '13200', '12500', '5600', '7000', '11900', '10400', '10700',
        '12700', '6800', '6500', '13600', '10200', '9000', '14900', '8200',
        '15200', '5000', '16300', '12400', '\t8400', '10500', '4200',
        '4700', '10900', '8100', '9500', '2200', '12800', '11200', '19100',
        '\t?', '12300', '16700', '2600', '26400', '8800', '7400', '4900',
        '8000', '12000', '15700', '4100', '5700', '11500', '5400', '10800',
        '9900', '5200', '5900', '9300', '9700', '5100', '6600'],
        dtype=object)}
{'red_blood_cell_count': array(['5.2', nan, '3.9', '4.6', '4.4', '5', '4.0', '3.7', '3.8', '3.4',
        '2.6', '2.8', '4.3', '3.2', '3.6', '4', '4.1', '4.9', '2.5', '4.2',
        '4.5', '3.1', '4.7', '3.5', '6.0', '5.0', '2.1', '5.6', '2.3',
        '2.9', '2.7', '8.0', '3.3', '3.0', '3', '2.4', '4.8', '\t?', '5.4',
        '6.1', '6.2', '6.3', '5.1', '5.8', '5.5', '5.3', '6.4', '5.7',
        '5.9', '6.5'], dtype=object)}
{'hypertension': array(['yes', 'no', nan], dtype=object)}
{'coronary_artery_disease': array(['no', 'yes', '\tno', nan], dtype=object)}
{'appetite': array(['good', 'poor', nan], dtype=object)}
{'peda_edema': array(['no', 'yes', nan], dtype=object)}
{'aanemia': array(['no', 'yes', nan], dtype=object)}
{'class': array(['ckd', 'ckd\t', 'notckd'], dtype=object)}
```

```
In [13]: ### Finding numerical variables
colname_num = [var for var in df1.columns if df1[var].dtype!='O']
print('There are {} numerical variables\n'.format(len(colname_num)))
print('The numerical variables are :', colname_num)
```

There are 11 numerical variables

The numerical variables are : ['age', 'blood_pressure', 'specific_gravity', 'albumin', 'sugar', 'blood_glucose_random', 'blood_urea', 'serum_creatinine', 'sodium', 'potassium', 'haemoglobin']


```
In [14]: # Looking at unique values in numerical columns
for col in colname_num:
    print(f"{col} has {df1[col].unique()} values\n")
```

age has [48. 7. 62. 51. 60. 68. 24. 52. 53. 50. 63. 40. 47. 61. 21. 42. 75. 69. nan 73. 70. 65. 76. 72. 82. 46. 45. 35. 54. 11. 59. 67. 15. 55. 44. 26. 64. 56. 5. 74. 38. 58. 71. 34. 17. 12. 43. 41. 57. 8. 39. 66. 81. 14. 27. 83. 30. 4. 3. 6. 32. 80. 49. 90. 78. 19. 2. 33. 36. 37. 23. 25. 20. 29. 28. 22. 79.] values

blood_pressure has [80. 50. 70. 90. nan 100. 60. 110. 140. 180. 120.] values

specific_gravity has [1.02 1.01 1.005 1.015 nan 1.025] values

albumin has [1. 4. 2. 3. 0. nan 5.] values

sugar has [0. 3. 4. 1. nan 2. 5.] values

blood_glucose_random has [121. nan 423. 117. 106. 74. 100. 410. 138. 70. 490. 380. 208. 98. 157. 76. 99. 114. 263. 173. 95. 108. 156. 264. 123. 93. 107. 159. 140. 171. 270. 92. 137. 204. 79. 207. 124. 144. 91. 162. 246. 253. 141. 182. 86. 150. 146. 425. 112. 250. 360. 163. 129. 133. 102. 158. 165. 132. 104. 127. 415. 169. 251. 109. 280. 210. 219. 295. 94. 172. 101. 298. 153. 88. 226. 143. 115. 89. 297. 233. 294. 323. 125. 90. 308. 118. 224. 128. 122. 214. 213. 268. 256. 84. 105. 288. 139. 78. 273. 242. 424. 303. 148. 160. 192. 307. 220. 447. 309. 22. 111. 261. 215. 234. 131. 352. 80. 239. 110. 130. 184. 252. 113. 230. 341. 255. 103. 238. 248. 120. 241. 269. 201. 203. 463. 176. 82. 119. 97. 96. 81. 116. 134. 85. 83. 87. 75.] values

blood_urea has [36. 18. 53. 56. 26. 25. 54. 31. 60. 107. 55. 72. 86. 90. 162. 46. 87. 27. 148. 180. 163. nan 50. 75. 45. 28. 155. 33. 39. 153. 29. 65. 103. 70. 80. 20. 202. 77. 89. 24. 17. 32. 114. 66. 38. 164. 142. 96. 391. 15. 111. 73. 19. 92. 35. 16. 139. 48. 85. 98. 186. 37. 47. 52. 82. 51. 106. 22. 217. 88. 118. 50.1 71. 34. 40. 21. 219. 30. 125. 166. 49. 208. 176. 68. 145. 165. 322. 23. 235. 132. 76. 42. 44. 41. 113. 1.5 146. 58. 133. 137. 67. 115. 223. 98.6 158. 94. 74. 150. 61. 57. 95. 191. 93. 241. 64. 79. 215. 309. 10.] values

serum_creatinine has [1.2 0.8 1.8 3.8 1.4 1.1 24. 1.9 7.2 4. 2.7 2.1 4.6 4.1 9.6 2.2 5.2 1.3 1.6 3.9 76. 7.7 nan 2.4 7.3 1.5 2.5 2. 3.4 0.7 1. 10.8 6.3 5.9 0.9 3. 3.25 9.7 6.4 3.2 32. 0.6 6.1 3.3 6.7 8.5 2.8 15. 2.9 1.7 3.6 5.6 6.5 4.4 10.2 11.5 0.5 12.2 5.3 9.2 13.8 16.9 6. 7.1 18. 2.3 13. 48.1 14.2 16.4 2.6 7.5 4.3 18.1 11.8 9.3 6.8 13.5 12.8 11.9 12. 13.4 15.2 13.3 0.4] values

sodium has [nan 111. 142. 104. 114. 131. 138. 135. 130. 141. 139. 4.5 136. 129. 140. 132. 133. 134. 125. 163. 137. 128. 143. 127. 146. 126. 122. 147. 124. 115. 145. 113. 120. 150. 144.] values

potassium has [nan 2.5 3.2 4. 3.7 4.2 5.8 3.4 6.4 4.9 4.1 4.3 5.2 3.8 4.6 3.9 4.7 5.9 4.8 4.4 6.6 39. 5.5 5. 3.5 3.6 7.6 2.9 4.5 5.7 5.4 5.3 47. 6.3 5.1 5.6 3. 2.8 2.7 6.5 3.3] values

haemoglobin has [15.4 11.3 9.6 11.2 11.6 12.2 12.4 10.8 9.5 9.4 9.7 9.8 5.6 7.6 12.6 12.1 12.7 10.3 7.7 10.9 nan 11.1 9.9 12.5 12.9 10.1 12. 13. 7.9 9.3 15. 10. 8.6 13.6 10.2 10.5 6.6 11. 7.5 15.6 15.2 4.8 9.1 8.1 11.9 13.5 8.3 7.1 16.1 10.4 9.2 6.2 13.9 14.1 6. 11.8 11.7 11.4 14. 8.2 13.2 6.1 8. 12.3 8.4 14.3 9. 8.7 10.6 13.1 10.7 5.5 5.8 6.8 8.8 8.5 13.8 11.5 7.3 13.7 12.8 13.4 6.3 3.1 17. 15.9 14.5 15.5 16.2 14.4 14.2 16.3 14.8 16.5 15.7 13.3 14.6 16.4 16.9 16. 14.7 16.6 14.9 16.7 16.8 15.8 15.1 17.1 17.2 15.3 17.3 17.4 17.7 17.8 17.5 17.6] values

```
In [15]: ### Finding categorical variables
colname_cat = [var for var in df1.columns if df1[var].dtype=='O']
print('There are {} categorical variables\n'.format(len(colname_cat)))
print('The categorical variables are :', colname_cat)
```

There are 13 categorical variables

The categorical variables are : ['red_blood_cells', 'pus_cell', 'pus_cell_clumps', 'bacteria', 'packed_cell_volume', 'white_blood_cell_count', 'red_blood_cell_count', 'hypertension', 'coronary_artery_disease', 'appetite', 'peda_edema', 'aanemia', 'class']

```
In [16]: ### Converting necessary columns to numerical type
df1['packed_cell_volume'] = pd.to_numeric(df1['packed_cell_volume'], errors='coerce')
df1['white_blood_cell_count'] = pd.to_numeric(df1['white_blood_cell_count'], errors='coerce')
df1['red_blood_cell_count'] = pd.to_numeric(df1['red_blood_cell_count'], errors='coerce')
df1.dtypes
```

Out[16]: age float64
blood_pressure float64
specific_gravity float64
albumin float64
sugar float64
red_blood_cells object
pus_cell object
pus_cell_clumps object
bacteria object
blood_glucose_random float64
blood_urea float64
serum_creatinine float64
sodium float64
potassium float64
haemoglobin float64
packed_cell_volume float64
white_blood_cell_count float64
red_blood_cell_count float64
hypertension object
coronary_artery_disease object
appetite object
peda_edema object
aanemia object
class object
dtype: object

```
In [17]: # Looking at unique values in categorical columns
for col in colname_cat:
    print(f"{col} has {df1[col].unique()} values\n")
```

red_blood_cells has [nan 'normal' 'abnormal'] values

pus_cell has ['normal' 'abnormal' nan] values

pus_cell_clumps has ['notpresent' 'present' nan] values

bacteria has ['notpresent' 'present' nan] values

packed_cell_volume has [44. 38. 31. 32. 35. 39. 36. 33. 29. 28. nan 16. 24. 37. 30. 34. 40. 45. 27. 48. 52. 14. 22. 18. 42. 17. 46. 23. 19. 25. 41. 26. 15. 21. 43. 20. 47. 9. 49. 50. 53. 51. 54.] values

white_blood_cell_count has [7800. 6000. 7500. 6700. 7300. nan 6900. 9600. 12100. 4500. 12200. 11000. 3800. 11400. 5300. 9200. 6200. 8300. 8400. 10300. 9800. 9100. 7900. 6400. 8600. 18900. 21600. 4300. 8500. 11300. 7200. 7700. 14600. 6300. 7100. 11800. 9400. 5500. 5800. 13200. 12500. 5600. 7000. 11900. 10400. 10700. 12700. 6800. 6500. 13600. 10200. 9000. 14900. 8200. 15200. 5000. 16300. 12400. 10500. 4200. 4700. 10900. 8100. 9500. 2200. 12800. 11200. 19100. 12300. 16700. 2600. 26400. 8800. 7400. 4900. 8000. 12000. 15700. 4100. 5700. 11500. 5400. 10800. 9900. 5200. 5900. 9300. 9700. 5100. 6600.] values

red_blood_cell_count has [5.2 nan 3.9 4.6 4.4 5. 4. 3.7 3.8 3.4 2.6 2.8 4.3 3.2 3.6 4.1 4.9 2.5 4.2 4.5 3.1 4.7 3.5 6. 2.1 5.6 2.3 2.9 2.7 8. 3.3 3. 2.4 4.8 5.4 6.1 6.2 6.3 5.1 5.8 5.5 5.3 6.4 5.7 5.9 6.5] values

hypertension has ['yes' 'no' nan] values

coronary_artery_disease has ['no' 'yes' '\tno' nan] values

appetite has ['good' 'poor' nan] values

peda_edema has ['no' 'yes' nan] values

aanemia has ['no' 'yes' nan] values

class has ['ckd' 'ckd\t' 'notckd'] values

```
In [18]: ### Cleaning categorical columns

df1['coronary_artery_disease'] = df1['coronary_artery_disease'].replace(to_replace = '\tno', value='no')
df1['class'] = df1['class'].replace(to_replace = {'ckd\t': 'ckd', 'notckd': 'not ckd'})
```

```
In [19]: colname_num = [var for var in df1.columns if df1[var].dtype!='O']
colname_cat = [var for var in df1.columns if df1[var].dtype=='O']
print(colname_cat)
print(colname_num)

['red_blood_cells', 'pus_cell', 'pus_cell_clumps', 'bacteria', 'hypertension', 'coronary_artery_disease', 'appetite', 'peda_edema', 'aanemia', 'class']
['age', 'blood_pressure', 'specific_gravity', 'albumin', 'sugar', 'blood_glucose_random', 'blood_urea', 'serum_creatinine', 'sodium', 'potassium', 'haemoglobin', 'packed_cell_vol
ume', 'white_blood_cell_count', 'red_blood_cell_count']
```

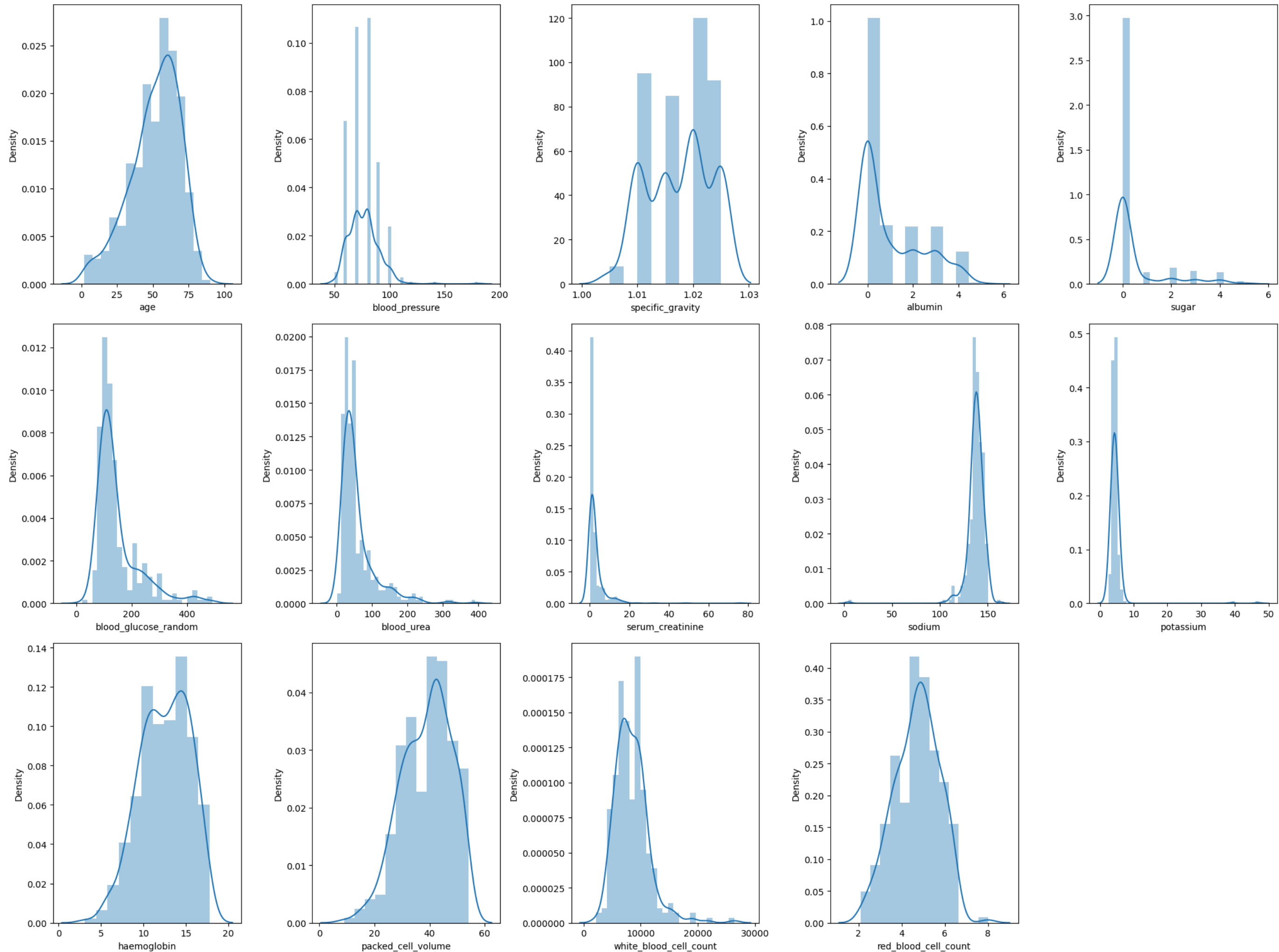
In [20]: *### Checking numerical features distribution*

```
plt.figure(figsize = (20, 15))
plotnumber = 1

for column in colname_num:
    if plotnumber <= 14:
        ax = plt.subplot(3, 5, plotnumber)
        sns.distplot(df1[column])
        plt.xlabel(column)

    plotnumber += 1

plt.tight_layout()
plt.show()
```



In [21]: df2 = df1.copy()
df2.shape

Out[21]: (400, 24)

In [22]: df2.isna().sum()

Out[22]: age 9
blood_pressure 12
specific_gravity 47
albumin 46
sugar 49
red_blood_cells 152
pus_cell 65
pus_cell_clumps 4
bacteria 4
blood_glucose_random 44
blood_urea 19
serum_creatinine 17
sodium 87
potassium 88
haemoglobin 52
packed_cell_volume 71
white_blood_cell_count 106
red_blood_cell_count 131
hypertension 2
coronary_artery_disease 2
appetite 1
peda_edema 1
aanemia 1
class 0
dtype: int64

```
In [23]: for i in colname_num:
        print("Column Names: ", i)
        print("Null Values: ", df2[i].isna().sum())
        print("Mean Values: ",df2[i].mean())
        print("Median Values: ",df2[i].median())
        print("Mode Values: ",df2[i].mode())
        print('-' * 50)
```

Column Names: age
Null Values: 9
Mean Values: 51.48337595907928
Median Values: 55.0
Mode Values: 0 60.0
Name: age, dtype: float64

Column Names: blood_pressure
Null Values: 12
Mean Values: 76.46907216494846
Median Values: 80.0
Mode Values: 0 80.0
Name: blood_pressure, dtype: float64

Column Names: specific_gravity
Null Values: 47
Mean Values: 1.0174079320113314
Median Values: 1.02
Mode Values: 0 1.02
Name: specific_gravity, dtype: float64

Column Names: albumin
Null Values: 46
Mean Values: 1.0169491525423728
Median Values: 0.0
Mode Values: 0 0.0
Name: albumin, dtype: float64

Column Names: sugar
Null Values: 49
Mean Values: 0.45014245014245013
Median Values: 0.0
Mode Values: 0 0.0
Name: sugar, dtype: float64

Column Names: blood_glucose_random
Null Values: 44
Mean Values: 148.0365168539326
Median Values: 121.0
Mode Values: 0 99.0
Name: blood_glucose_random, dtype: float64

Column Names: blood_urea
Null Values: 19
Mean Values: 57.425721784776904
Median Values: 42.0
Mode Values: 0 46.0
Name: blood_urea, dtype: float64

Column Names: serum_creatinine
Null Values: 17
Mean Values: 3.072454308093995
Median Values: 1.3
Mode Values: 0 1.2
Name: serum_creatinine, dtype: float64

Column Names: sodium
Null Values: 87
Mean Values: 137.52875399361022
Median Values: 138.0
Mode Values: 0 135.0
Name: sodium, dtype: float64

Column Names: potassium
Null Values: 88
Mean Values: 4.62724358974359
Median Values: 4.4
Mode Values: 0 3.5
1 5.0
Name: potassium, dtype: float64

Column Names: haemoglobin
Null Values: 52
Mean Values: 12.526436781609195
Median Values: 12.649999999999999
Mode Values: 0 15.0
Name: haemoglobin, dtype: float64

Column Names: packed_cell_volume
Null Values: 71
Mean Values: 38.88449848024316
Median Values: 40.0
Mode Values: 0 41.0
1 52.0
Name: packed_cell_volume, dtype: float64

Column Names: white_blood_cell_count
Null Values: 106
Mean Values: 8406.122448979591
Median Values: 8000.0
Mode Values: 0 9800.0
Name: white_blood_cell_count, dtype: float64

Column Names: red_blood_cell_count
Null Values: 131
Mean Values: 4.707434944237917
Median Values: 4.8
Mode Values: 0 5.2
Name: red_blood_cell_count, dtype: float64

```
In [24]: df2['age'] = df2['age'].fillna(df2['age'].median())
df2['blood_pressure'] = df2['blood_pressure'].fillna(df2['blood_pressure'].median())
df2['specific_gravity'] = df2['specific_gravity'].fillna(df2['specific_gravity'].median())
df2['albumin'] = df2['albumin'].fillna(df2['albumin'].mean())
df2['sugar'] = df2['sugar'].fillna(df2['sugar'].mean())
df2['blood_glucose_random'] = df2['blood_glucose_random'].fillna(df2['blood_glucose_random'].median())
df2['blood_urea'] = df2['blood_urea'].fillna(df2['blood_urea'].mean())
df2['serum_creatinine'] = df2['serum_creatinine'].fillna(df2['serum_creatinine'].mean())
df2['sodium'] = df2['sodium'].fillna(df2['sodium'].mean())
df2['potassium'] = df2['potassium'].fillna(df2['potassium'].mean())
df2['haemoglobin'] = df2['haemoglobin'].fillna(df2['haemoglobin'].mean())
df2['packed_cell_volume'] = df2['packed_cell_volume'].fillna(df2['packed_cell_volume'].mean())
df2['white_blood_cell_count'] = df2['white_blood_cell_count'].fillna(df2['white_blood_cell_count'].median())
df2['red_blood_cell_count'] = df2['red_blood_cell_count'].fillna(df2['red_blood_cell_count'].median())
df2.isna().sum()
```

```
Out[24]: age                0
blood_pressure            0
specific_gravity          0
albumin                   0
sugar                     0
red_blood_cells          152
pus_cell                  65
pus_cell_clumps           4
bacteria                  4
blood_glucose_random      0
blood_urea                0
serum_creatinine          0
sodium                   0
potassium                 0
haemoglobin               0
packed_cell_volume        0
white_blood_cell_count    0
red_blood_cell_count      0
hypertension              2
coronary_artery_disease   2
appetite                  1
peda_edema                1
aanemia                   1
class                     0
dtype: int64
```

```
In [25]: for i in colname_cat:
print("Column Names: ", i)
print("Unique : ", df2[i].unique())
print("Null Values: ", df2[i].isna().sum())
print("Mode Values: ",df2[i].mode())
print('-' * 50)
```

```
Column Names: red_blood_cells
Unique : [nan 'normal' 'abnormal']
Null Values: 152
Mode Values: 0 normal
Name: red_blood_cells, dtype: object
-----

Column Names: pus_cell
Unique : ['normal' 'abnormal' nan]
Null Values: 65
Mode Values: 0 normal
Name: pus_cell, dtype: object
-----

Column Names: pus_cell_clumps
Unique : ['notpresent' 'present' nan]
Null Values: 4
Mode Values: 0 notpresent
Name: pus_cell_clumps, dtype: object
-----

Column Names: bacteria
Unique : ['notpresent' 'present' nan]
Null Values: 4
Mode Values: 0 notpresent
Name: bacteria, dtype: object
-----

Column Names: hypertension
Unique : ['yes' 'no' nan]
Null Values: 2
Mode Values: 0 no
Name: hypertension, dtype: object
-----

Column Names: coronary_artery_disease
Unique : ['no' 'yes' nan]
Null Values: 2
Mode Values: 0 no
Name: coronary_artery_disease, dtype: object
-----

Column Names: appetite
Unique : ['good' 'poor' nan]
Null Values: 1
Mode Values: 0 good
Name: appetite, dtype: object
-----

Column Names: peda_edema
Unique : ['no' 'yes' nan]
Null Values: 1
Mode Values: 0 no
Name: peda_edema, dtype: object
-----

Column Names: aanemia
Unique : ['no' 'yes' nan]
Null Values: 1
Mode Values: 0 no
Name: aanemia, dtype: object
-----

Column Names: class
Unique : ['ckd' 'not ckd']
Null Values: 0
Mode Values: 0 ckd
Name: class, dtype: object
-----
```

In [26]: df2['red_blood_cells'] = df2['red_blood_cells'].fillna(df2['red_blood_cells'].mode()[0])
df2['pus_cell'] = df2['pus_cell'].fillna(df2['pus_cell'].mode()[0])
df2['pus_cell_clumps'] = df2['pus_cell_clumps'].fillna(df2['pus_cell_clumps'].mode()[0])
df2['bacteria'] = df2['bacteria'].fillna(df2['bacteria'].mode()[0])
df2['hypertension'] = df2['hypertension'].fillna(df2['hypertension'].mode()[0])
df2['coronary_artery_disease'] = df2['coronary_artery_disease'].fillna(df2['coronary_artery_disease'].mode()[0])
df2['appetite'] = df2['appetite'].fillna(df2['appetite'].mode()[0])
df2['peda_edema'] = df2['peda_edema'].fillna(df2['peda_edema'].mode()[0])
df2['aanemia'] = df2['aanemia'].fillna(df2['aanemia'].mode()[0])
df2.isna().sum()

Out[26]: age 0
blood_pressure 0
specific_gravity 0
albumin 0
sugar 0
red_blood_cells 0
pus_cell 0
pus_cell_clumps 0
bacteria 0
blood_glucose_random 0
blood_urea 0
serum_creatinine 0
sodium 0
potassium 0
haemoglobin 0
packed_cell_volume 0
white_blood_cell_count 0
red_blood_cell_count 0
hypertension 0
coronary_artery_disease 0
appetite 0
peda_edema 0
aanemia 0
class 0
dtype: int64

In [27]: *### Converting all categorical data into numerical data*
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for x in colname_cat:
 df2[x]=le.fit_transform(df2[x])
 le_name_mapping = dict(zip(le.classes_, le.transform(le.classes_)))
 print("Feature",x)
 print("Mapping", le_name_mapping)

Feature red_blood_cells
Mapping {'abnormal': 0, 'normal': 1}
Feature pus_cell
Mapping {'abnormal': 0, 'normal': 1}
Feature pus_cell_clumps
Mapping {'notpresent': 0, 'present': 1}
Feature bacteria
Mapping {'notpresent': 0, 'present': 1}
Feature hypertension
Mapping {'no': 0, 'yes': 1}
Feature coronary_artery_disease
Mapping {'no': 0, 'yes': 1}
Feature appetite
Mapping {'good': 0, 'poor': 1}
Feature peda_edema
Mapping {'no': 0, 'yes': 1}
Feature aanemia
Mapping {'no': 0, 'yes': 1}
Feature class
Mapping {'ckd': 0, 'not ckd': 1}

In [28]: df2.head(15)

Out[28]:

	age	blood_pressure	specific_gravity	albumin	sugar	red_blood_cells	pus_cell	pus_cell_clumps	bacteria	blood_glucose_random	...	haemoglobin	packed_cell_volume	white_blood_cell_count	red_blood_cell_coun
0	48.0	80.0	1.020	1.000000	0.000000	1	1	0	0	121.0	...	15.4	44.000000	7800.0	5.
1	7.0	50.0	1.020	4.000000	0.000000	1	1	0	0	121.0	...	11.3	38.000000	6000.0	4.
2	62.0	80.0	1.010	2.000000	3.000000	1	1	0	0	423.0	...	9.6	31.000000	7500.0	4.
3	48.0	70.0	1.005	4.000000	0.000000	1	0	1	0	117.0	...	11.2	32.000000	6700.0	3.
4	51.0	80.0	1.010	2.000000	0.000000	1	1	0	0	106.0	...	11.6	35.000000	7300.0	4.
5	60.0	90.0	1.015	3.000000	0.000000	1	1	0	0	74.0	...	12.2	39.000000	7800.0	4.
6	68.0	70.0	1.010	0.000000	0.000000	1	1	0	0	100.0	...	12.4	36.000000	8000.0	4.
7	24.0	80.0	1.015	2.000000	4.000000	1	0	0	0	410.0	...	12.4	44.000000	6900.0	5.
8	52.0	100.0	1.015	3.000000	0.000000	1	0	1	0	138.0	...	10.8	33.000000	9600.0	4.
9	53.0	90.0	1.020	2.000000	0.000000	0	0	1	0	70.0	...	9.5	29.000000	12100.0	3.
10	50.0	60.0	1.010	2.000000	4.000000	1	0	1	0	490.0	...	9.4	28.000000	8000.0	4.
11	63.0	70.0	1.010	3.000000	0.000000	0	0	1	0	380.0	...	10.8	32.000000	4500.0	3.
12	68.0	70.0	1.015	3.000000	1.000000	1	1	1	0	208.0	...	9.7	28.000000	12200.0	3.
13	68.0	70.0	1.020	1.016949	0.450142	1	1	0	0	98.0	...	9.8	38.884498	8000.0	4.
14	68.0	80.0	1.010	3.000000	2.000000	1	0	1	1	157.0	...	5.6	16.000000	11000.0	2.

15 rows × 24 columns

```
In [29]: for col in df2.columns:
        print(f"{col} has {df2[col].nunique()} categories\n")
```

age has 76 categories

blood_pressure has 10 categories

specific_gravity has 5 categories

albumin has 7 categories

sugar has 7 categories

red_blood_cells has 2 categories

pus_cell has 2 categories

pus_cell_clumps has 2 categories

bacteria has 2 categories

blood_glucose_random has 146 categories

blood_urea has 119 categories

serum_creatinine has 85 categories

sodium has 35 categories

potassium has 41 categories

haemoglobin has 116 categories

packed_cell_volume has 43 categories

white_blood_cell_count has 89 categories

red_blood_cell_count has 45 categories

hypertension has 2 categories

coronary_artery_disease has 2 categories

appetite has 2 categories

peda_edema has 2 categories

aanemia has 2 categories

class has 2 categories

```
In [30]: df3 = df2.copy()
df3.columns
```

Out[30]: Index(['age', 'blood_pressure', 'specific_gravity', 'albumin', 'sugar', 'red_blood_cells', 'pus_cell', 'pus_cell_clumps', 'bacteria', 'blood_glucose_random', 'blood_urea', 'serum_creatinine', 'sodium', 'potassium', 'haemoglobin', 'packed_cell_volume', 'white_blood_cell_count', 'red_blood_cell_count', 'hypertension', 'coronary_artery_disease', 'appetite', 'peda_edema', 'aanemia', 'class'], dtype='object')

```
In [31]: ### Spliting Data into X and y
X = df3.values[:, :-1]
y = df3.values[:, -1]
print('X:', X.shape)
print('*' * 13)
print('y:', y.shape)

X: (400, 23)
*****
y: (400,)
```

```
In [32]: ### Feature Scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
#x = scaler.fit_transform(x)
print(X)

[[-0.21003135  0.25421378  0.4214856  ... -0.50780078 -0.4843221
 -0.42008403]
 [-2.62723421 -1.97247624  0.4214856  ... -0.50780078 -0.4843221
 -0.42008403]
 [ 0.615355   0.25421378 -1.4210744  ...  1.96927621 -0.4843221
  2.38047614]
 ...
 [-2.33245337  0.25421378  0.4214856  ... -0.50780078 -0.4843221
 -0.42008403]
 [-2.03767254 -1.23024623  1.3427656  ... -0.50780078 -0.4843221
 -0.42008403]
 [ 0.37953033  0.25421378  1.3427656  ... -0.50780078 -0.4843221
 -0.42008403]]
```

```
In [33]: y = y.astype(int) ### convert y in to integer always perform this operation
```

```
In [34]: ### Spliting into Training and Testing Data
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=42)

print("X_train: ",X_train.shape)
print("X_test: ",X_test.shape)
print("y_train: ",y_train.shape)
print("y_test: ",y_test.shape)

X_train: (320, 23)
X_test: (80, 23)
y_train: (320,)
y_test: (80,)
```

```
In [35]: #importing model
from catboost import CatBoostClassifier
#create a model object
model_cat = CatBoostClassifier(iterations=10)
#train the model object
model_cat.fit(X_train,y_train)
#predict using the model
y_pred = model_cat.predict(X_test)
print(y_pred)

Learning rate set to 0.432149
0:   learn: 0.1978358      total: 149ms   remaining: 1.34s
1:   learn: 0.1112342      total: 154ms   remaining: 617ms
2:   learn: 0.0659861      total: 159ms   remaining: 371ms
3:   learn: 0.0398560      total: 163ms   remaining: 245ms
4:   learn: 0.0284298      total: 167ms   remaining: 167ms
5:   learn: 0.0219237      total: 170ms   remaining: 113ms
6:   learn: 0.0167853      total: 173ms   remaining: 74.2ms
7:   learn: 0.0156189      total: 176ms   remaining: 44ms
8:   learn: 0.0138802      total: 179ms   remaining: 19.9ms
9:   learn: 0.0112901      total: 181ms   remaining: 0us
[0 1 0 0 0 0 1 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 1 1 1 1 0 0 1 0 1 0 1 0 0 0 0
 1 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 1 1 0 0 0 1 1 1 0 1 0 0 0
 1 0 0 1 0 1]
```

```
In [36]: # Checking confusion matrix for the model
cfm = confusion_matrix(y_test,y_pred)
dff = pd.DataFrame(cfm)
dff.style.set_properties(**{"background-color": "#F3FFFF", "color": "black", "border": "2px solid black"})
```

Out[36]:

	0	1
0	51	1
1	0	28

```
In [37]: # Checking classification report score for the model
cr = classification_report(y_test,y_pred)
print("Classification report: ")
print(cr)

# Checking accuracy score for the model
acc = accuracy_score(y_test,y_pred)
print("Accuracy of the model: ",acc)

Classification report:
              precision    recall  f1-score   support

         0       1.00      0.98      0.99         52
         1       0.97      1.00      0.98         28

   accuracy              0.99              80
  macro avg       0.98      0.99      0.99              80
 weighted avg       0.99      0.99      0.99              80

Accuracy of the model:  0.9875
```

```
In [ ]:
```