```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
sns.set()
plt.style.use('ggplot')
%matplotlib inline
df = pd.read_csv("kidney_disease.csv")
df.head(10)
 ₹
         id
              age
                      bp
                             sg
                                 al
                                      su
                                               rbc
                                                                                                  wc
                                                                                                        rc
                                                                                                           htn
                                                                                                                  dm
                                                                                                                     cad
                                                                                                                           appet
                                                                                                                                   pe
                                                                                                                                       ane
                                                                                                                                           classific
      0
          0
             48.0
                    0.08
                         1.020
                                1.0
                                     0.0
                                              NaN
                                                      normal
                                                              notpresent notpresent
                                                                                          44
                                                                                               7800
                                                                                                       5.2
                                                                                                            yes
                                                                                                                 yes
                                                                                                                       no
                                                                                                                            good
                                                                                                                                   no
                                                                                                                                        no
          1
              7.0
                    50.0
                         1.020
                                4.0
                                     0.0
                                              NaN
                                                                                          38
                                                                                                6000
                                                                                                      NaN
                                                      normal
                                                              notpresent notpresent
                                                                                                             no
                                                                                                                  no
                                                                                                                       no
                                                                                                                            good
                                                                                                                                   no
                                                                                                                                        no
             62.0
      2
          2
                    0.08
                         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
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          4
             51.0
                    0.08
                         1.010 2.0
                                     0.0
                                            normal
                                                      normal
                                                              notpresent
                                                                         notpresent
                                                                                          35
                                                                                                7300
                                                                                                       4.6
                                                                                                             no
                                                                                                                  no
                                                                                                                       no
                                                                                                                            good
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                                                                                                                                        no
          5
             60.0
                         1.015 3.0
                    90.0
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                                              NaN
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                                                              notpresent notpresent
                                                                                          39
                                                                                                7800
                                                                                                       4.4
                                                                                                            yes
                                                                                                                yes
                                                                                                                       no
                                                                                                                            good
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          6
             68.0
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                                                                                          36
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          7
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                                                    abnormal
                                                              notpresent
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                                                                                                         5
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                                                                                                                yes
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                                                                                                                                        no
          8
             52.0
                   100.0
                         1.015 3.0
                                                                                                9600
                                    0.0
                                                                                          33
                                            normal
                                                    abnormal
                                                                present
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                                                                                                                            aood
                                                                                                                                   no
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          9
             53.0
                    90.0 1.020 2.0 0.0 abnormal
                                                                                          29
                                                                                              12100
                                                                                                       3.7
                                                                                                            yes
                                                    abnormal
                                                                present notpresent
                                                                                                                yes
                                                                                                                       no
                                                                                                                            poor
                                                                                                                                   no
                                                                                                                                       yes
      10 rows × 26 columns
df['classification'].value_counts()
                248
     ckd
     notckd
                150
     ckd\t
     Name: classification, dtype: int64
df.shape
→ (400, 26)
df.drop('id',axis=1, inplace=True)
df.head()
 ₹
          age
                bp
                            al
                                       rbc
                                                                         ba
                                                                               bgr
                                                                                                      rc
                                                                                                          htn
                                                                                                                dm
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                                                                                                                         appet
                                                                                                                                    ane classificat
                       sg
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      0 48.0 80.0
                    1.020
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                                               normal
                                                      notpresent notpresent
                                                                             121.0
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                                                                                                     5.2
                                                                                                                          good
                                                                                                          yes
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                                                                                                                     no
          7.0
              50.0
                    1.020 4.0 0.0
                                                                              NaN
                                                                                          38
                                                                                              6000
                                                                                                    NaN
                                       NaN
                                               normal
                                                      notpresent notpresent
                                                                                                                          aood
                                                                                                           no
                                                                                                                no
                                                                                                                     no
                                                                                                                                 no
                                                                                                                                       no
              80.0
                    1.010 2.0 3.0 normal
                                               normal
                                                      notpresent notpresent
                                                                            423.0
                                                                                          31
                                                                                              7500
                                                                                                    NaN
                                                                                                           no
                                                                                                               yes
                                                                                                                     no
                                                                                                                           poor
                                                                                                                                 no
                                                                                                                                     yes
         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
      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
     5 rows × 25 columns
df.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']
```

df.head()

₹		age	blood_pressure	specific_gravity	albumin	sugar	red_blood_cells	pus_cell	pus_cell_clumps	bacteria	blood_glucose_random	• •
	0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	121.0	
	1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	NaN	
	2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	423.0	
	3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	117.0	
	4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	106.0	

df.describe()

5 rows × 25 columns

		age	blood_pressure	specific_gravity	albumin	sugar	blood_glucose_random	blood_urea	serum_creatinine	sodiu
	count	391.000000	388.000000	353.000000	354.000000	351.000000	356.000000	381.000000	383.000000	313.00000
	mean	51.483376	76.469072	1.017408	1.016949	0.450142	148.036517	57.425722	3.072454	137.52875
	std	17.169714	13.683637	0.005717	1.352679	1.099191	79.281714	50.503006	5.741126	10.40875
	min	2.000000	50.000000	1.005000	0.000000	0.000000	22.000000	1.500000	0.400000	4.50000
	25%	42.000000	70.000000	1.010000	0.000000	0.000000	99.000000	27.000000	0.900000	135.00000
	50%	55.000000	80.000000	1.020000	0.000000	0.000000	121.000000	42.000000	1.300000	138.00000
	75%	64.500000	80.000000	1.020000	2.000000	0.000000	163.000000	66.000000	2.800000	142.00000
	max	90.000000	180.000000	1.025000	5.000000	5.000000	490.000000	391.000000	76.000000	163.00000

df.info()

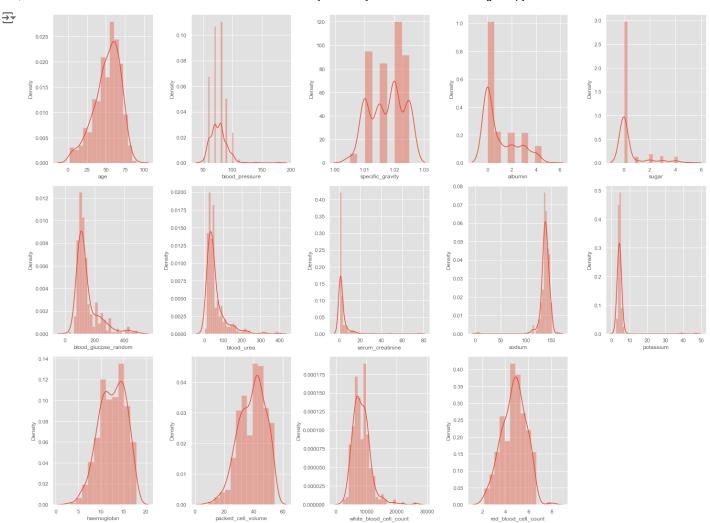
```
<class 'pandas.core.frame.DataFrame'>
     RangeIndex: 400 entries, 0 to 399
     Data columns (total 25 columns):
     # Column
                                  Non-Null Count Dtype
     ---
     0
                                   391 non-null
                                                  float64
         blood_pressure
                                   388 non-null
                                                  float64
         specific_gravity
                                  353 non-null
                                                  float64
                                  354 non-null
                                                  float64
         albumin
                                   351 non-null
                                                  float64
         sugar
         red_blood_cells
                                  248 non-null
                                                  object
      6
         pus_cell
                                  335 non-null
                                                  object
          pus_cell_clumps
                                  396 non-null
                                                  object
                                  396 non-null
                                                  object
         bacteria
                                  356 non-null
                                                  float64
         blood_glucose_random
                                  381 non-null
                                                  float64
     10 blood_urea
      11 serum_creatinine
                                  383 non-null
                                                  float64
      12 sodium
                                  313 non-null
                                                  float64
     13 potassium
                                  312 non-null
                                                  float64
      14 haemoglobin
                                  348 non-null
                                                  float64
      15
         packed_cell_volume
                                  330 non-null
                                                  object
     16 white blood cell count
                                  295 non-null
                                                  object
      17 red_blood_cell_count
                                  270 non-null
                                                  object
         hypertension
                                   398 non-null
                                                  object
      18
      19 diabetes_mellitus
                                  398 non-null
                                                  object
         coronary_artery_disease 398 non-null
                                                  object
      20
     21
         appetite
                                  399 non-null
                                                  object
      22 peda edema
                                  399 non-null
                                                  object
      23
         aanemia
                                  399 non-null
                                                  object
      24 class
                                  400 non-null
                                                  object
     dtypes: float64(11), object(14)
     memory usage: 78.2+ KB
df['packed_cell_volume'] = pd.to_numeric(df['packed_cell_volume'], errors='coerce')
df['white_blood_cell_count'] = pd.to_numeric(df['white_blood_cell_count'], errors='coerce')
df['red_blood_cell_count'] = pd.to_numeric(df['red_blood_cell_count'], errors='coerce')
df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 25 columns):

```
Non-Null Count
      #
          Column
                                                     Dtype
                                     391 non-null
                                                      float64
          age
          blood pressure
                                     388 non-null
                                                      float64
          specific_gravity
                                     353 non-null
                                                      float64
      3
          albumin
                                     354 non-null
                                                      float64
                                     351 non-null
                                                      float64
          sugar
         red_blood_cells
                                     248 non-null
                                                      object
                                                      object
          pus_cell
                                     335 non-null
          pus_cell_clumps
                                     396 non-null
                                                      object
          bacteria
                                     396 non-null
                                                      object
                                     356 non-null
                                                      float64
          blood_glucose_random
      10 blood_urea
                                     381 non-null
                                                      float64
      11 serum creatinine
                                     383 non-null
                                                      float64
                                     313 non-null
                                                      float64
      12 sodium
      13 potassium
                                    312 non-null
                                                      float64
      14 haemoglobin
                                    348 non-null
                                                      float64
      15 packed_cell_volume
                                     329 non-null
                                                      float64
      16 white_blood_cell_count 294 non-null
                                                      float64
      17 red_blood_cell_count
                                    269 non-null
                                                      float64
                                     398 non-null
                                                      object
      18 hypertension
      19 diabetes_mellitus
                                     398 non-null
                                                      object
      20 coronary_artery_disease 398 non-null
                                                      object
      21
          appetite
                                     399 non-null
                                                      object
      22 peda_edema
                                     399 non-null
                                                      object
      23 aanemia
                                     399 non-null
                                                      object
      24 class
                                     400 non-null
                                                      object
     dtypes: float64(14), object(11)
     memory usage: 78.2+ KB
df.columns
'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'],
           dtype='object')
cat_cols = [col for col in df.columns if df[col].dtype == 'object']
num_cols = [col for col in df.columns if df[col].dtype != 'object']
cat_cols
→ ['red_blood_cells',
       'pus_cell',
       'pus_cell_clumps',
      'bacteria',
      'hypertension'
      'diabetes_mellitus',
      'coronary_artery_disease',
      'appetite',
      'peda_edema',
      'aanemia',
      'class']
num_cols

→ ['age',
       'blood_pressure',
      'specific_gravity',
      'albumin',
      'sugar',
      'blood_glucose_random',
      'blood_urea',
      'serum_creatinine',
      'sodium',
       'potassium',
      'haemoglobin',
      'packed_cell_volume',
       'white blood cell count',
      'red_blood_cell_count']
for col in cat_cols:
   print(f"{col} has {df[col].unique()}")
```

```
→ red_blood_cells has [nan 'normal' 'abnormal']
     pus_cell has ['normal' 'abnormal' nan]
     pus_cell_clumps has ['notpresent' 'present' nan]
     bacteria has ['notpresent' 'present' nan]
     hypertension has ['yes' 'no' nan]
     diabetes_mellitus has ['yes' 'no' ' yes' '\tno' '\tyes' nan] coronary_artery_disease has ['no' 'yes' '\tno' nan]
     appetite has ['good' 'poor' nan]
peda_edema has ['no' 'yes' nan]
     aanemia has ['no' 'yes' nan]
     class has ['ckd' 'ckd\t' 'notckd']
df['diabetes_mellitus'].replace(to_replace = {'\tno':'no', '\tyes': 'yes', ' yes':'yes'}, inplace=True)
df['coronary_artery_disease'] = df['coronary_artery_disease'].replace(to_replace = '\tno', value = 'no')
df['class'] = df['class'].replace(to_replace={'ckd\t':'ckd', 'notckd': 'not ckd'})
cols = ['diabetes_mellitus', 'coronary_artery_disease', 'class']
for col in cols:
    print(f"{col} has {df[col].unique()}")
→ diabetes_mellitus has ['yes' 'no' nan]
     coronary_artery_disease has ['no' 'yes' nan] class has ['ckd' 'not ckd']
df['class'] = df['class'].map({'ckd':0, 'not ckd': 1})
df['class'] = pd.to_numeric(df['class'], errors = 'coerce')
cols = ['diabetes_mellitus', 'coronary_artery_disease', 'class']
for col in cols:
    print(f"{col} has {df[col].unique()}")
→ diabetes_mellitus has ['yes' 'no' nan]
     coronary_artery_disease has ['no' 'yes' nan]
     class has [0 1]
plt.figure(figsize = (20, 15))
plotnumber = 1
for column in num_cols:
    if plotnumber <= 14:
        ax = plt.subplot(3, 5, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column)
    plotnumber += 1
plt.tight_layout()
plt.show()
```

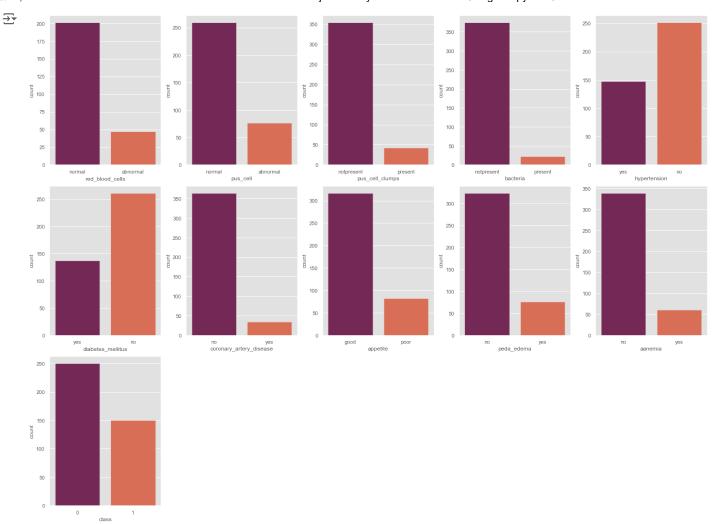


```
plt.figure(figsize = (20, 15))
plotnumber = 1

for column in cat_cols:
    if plotnumber <= 14:
        ax = plt.subplot(3, 5, plotnumber)
        sns.countplot(df[column] ,palette = 'rocket')
        plt.xlabel(column)

    plotnumber += 1

plt.tight_layout()
plt.show()</pre>
```



df.corr()



	age	blood_pressure	<pre>specific_gravity</pre>	albumin	sugar	blood_glucose_random	blood_urea	serum_creatinin
age	1.000000	0.159480	-0.191096	0.122091	0.220866	0.244992	0.196985	0.13253
blood_pressure	0.159480	1.000000	-0.218836	0.160689	0.222576	0.160193	0.188517	0.14622
specific_gravity	-0.191096	-0.218836	1.000000	-0.469760	-0.296234	-0.374710	-0.314295	-0.36147
albumin	0.122091	0.160689	-0.469760	1.000000	0.269305	0.379464	0.453528	0.39919
sugar	0.220866	0.222576	-0.296234	0.269305	1.000000	0.717827	0.168583	0.22324
blood_glucose_random	0.244992	0.160193	-0.374710	0.379464	0.717827	1.000000	0.143322	0.11487
blood_urea	0.196985	0.188517	-0.314295	0.453528	0.168583	0.143322	1.000000	0.58636
serum_creatinine	0.132531	0.146222	-0.361473	0.399198	0.223244	0.114875	0.586368	1.00000
sodium	-0.100046	-0.116422	0.412190	-0.459896	-0.131776	-0.267848	-0.323054	-0.69015
potassium	0.058377	0.075151	-0.072787	0.129038	0.219450	0.066966	0.357049	0.32610
haemoglobin	-0.192928	-0.306540	0.602582	-0.634632	-0.224775	-0.306189	-0.610360	-0.40167
packed_cell_volume	-0.242119	-0.326319	0.603560	-0.611891	-0.239189	-0.301385	-0.607621	-0.40419
white_blood_cell_count	0.118339	0.029753	-0.236215	0.231989	0.184893	0.150015	0.050462	-0.00639
red_blood_cell_count	-0.268896	-0.261936	0.579476	-0.566437	-0.237448	-0.281541	-0.579087	-0.40085
class	-0.227268	-0.294077	0.732163	-0.627090	-0.344070	-0.419672	-0.380605	-0.29996

```
plt.figure(figsize = (15,8))
sns.heatmap(df.corr(), annot=True, linewidth=2, linecolor = 'lightgray')
plt.show()
```



,															
age	1	0.16	-0.19	0.12	0.22	0.24	0.2	0.13	-0.1	0.058	-0.19	-0.24	0.12	-0.27	-0.23
blood_pressure	0.16	1	-0.22	0.16	0.22	0.16	0.19	0.15	-0.12	0.075	-0.31	-0.33	0.03	-0.26	-0.29
specific_gravity	-0.19	-0.22	1	-0.47	-0.3	-0.37	-0.31	-0.36	0.41	-0.073			-0.24	0.58	0.73
albumin	0.12	0.16	-0.47	1	0.27	0.38	0.45	0.4	-0.46	0.13	-0.63	-0.61	0.23	-0.57	-0.63
sugar	0.22	0.22	-0.3	0.27	1	0.72	0.17	0.22	-0.13	0.22	-0.22	-0.24	0.18	-0.24	-0.34
blood_glucose_random	0.24	0.16	-0.37	0.38	0.72	1	0.14	0.11	-0.27	0.067	-0.31	-0.3	0.15	-0.28	-0.42
blood_urea	0.2	0.19	-0.31	0.45	0.17	0.14	1	0.59	-0.32	0.36	-0.61	-0.61	0.05	-0.58	-0.38
serum_creatinine	0.13	0.15	-0.36	0.4	0.22	0.11	0.59	1	-0.69	0.33	-0.4	-0.4	-0.0064	-0.4	-0.3
sodium	-0.1	-0.12	0.41	-0.46	-0.13	-0.27	-0.32	-0.69	1	0.098	0.37	0.38	0.0073	0.34	0.38
potassium	0.058	0.075	-0.073	0.13	0.22	0.067	0.36	0.33	0.098	1	-0.13	-0.16	-0.11	-0.16	-0.085
haemoglobin	-0.19	-0.31	0.6	-0.63	-0.22	-0.31	-0.61	-0.4	0.37	-0.13	1	0.9	-0.17	0.8	0.77
packed_cell_volume	-0.24	-0.33	0.6	-0.61	-0.24	-0.3	-0.61	-0.4	0.38	-0.16	0.9	1	-0.2	0.79	0.74
white_blood_cell_count	0.12	0.03	-0.24	0.23	0.18	0.15	0.05	-0.0064	0.0073	-0.11	-0.17	-0.2	1	-0.16	-0.23
red_blood_cell_count	-0.27	-0.26	0.58	-0.57	-0.24	-0.28	-0.58	-0.4	0.34	-0.16	0.8	0.79	-0.16	1	0.7
dass	-0.23	-0.29	0.73	-0.63	-0.34	-0.42	-0.38	-0.3	0.38	-0.085	0.77	0.74	-0.23	0.7	1
	age	blood_pressure	specific_gravity	albumin	sugar	blood_glucose_random	blood_urea	serum_creatinine	sodium	potassium	haemoglobin	packed_cell_volume	white_blood_cell_count	red_blood_cell_count	dass

- 1.0 - 0.8 - 0.6 - 0.4 - 0.2 - 0.0 - -0.2 - -0.4 - -0.6

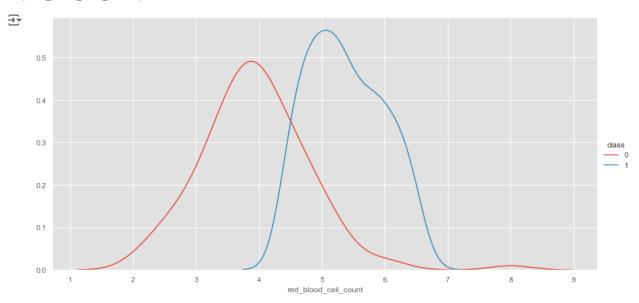
```
# EDA
```

```
def voilin(col):
    fig = px.violin(df, y=col, x='class', color='class', box=True, template='plotly_dark')
    return fig.show()

def kde(col):
    grid = sns.FacetGrid(df, hue='class', height = 6, aspect = 2)
    grid.map(sns.kdeplot, col)
    grid.add_legend()
```

```
def scatter_plot(col1, col2):
    fig = px.scatter(df, x=col1, y=col2, color="class", template='plotly_dark')
    return fig.show()
```

kde('red_blood_cell_count')



Data Preprocessing

checking for missing value
df.isnull().sum().sort_values(ascending=False)

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

df[num_cols].isnull().sum()

_ _	age	9
	blood_pressure	12
	specific_gravity	47
	albumin	46
	sugar	49
	blood_glucose_random	44
	blood_urea	19
	serum_creatinine	17
	sodium	87
	potassium	88
	haemoglobin	52
	<pre>packed_cell_volume</pre>	71
	white_blood_cell_count	106
	red_blood_cell_count dtype: int64	131

```
10/19/24, 1:21 PM
                                                         Advance Project Kidney Disease Prediction Using ML.ipynb - Colab
    df[cat_cols].isnull().sum()
     → red_blood_cells
                                     152
         pus_cell
                                      65
         pus cell clumps
                                       4
         bacteria
                                        4
         hypertension
                                        2
         diabetes_mellitus
                                        2
         coronary_artery_disease
         appetite
                                        1
         peda_edema
                                        1
         aanemia
                                        0
         class
         dtype: int64
    df.head()
    \rightarrow
             age
                  blood_pressure specific_gravity albumin sugar
                                                                      red_blood_cells pus_cell pus_cell_clumps
                                                                                                                    bacteria blood_glucose_random ..
          0 48.0
                              80.0
                                               1.020
                                                                  0.0
                                                           1.0
                                                                                  NaN
                                                                                           normal
                                                                                                         notpresent notpresent
                                                                                                                                               121.0
              7.0
                              50.0
                                               1.020
                                                           4.0
                                                                  0.0
                                                                                  NaN
                                                                                           normal
                                                                                                                                                NaN
                                                                                                         notpresent notpresent
          2 62.0
                              80.0
                                               1.010
                                                           2.0
                                                                  3.0
                                                                                normal
                                                                                           normal
                                                                                                         notpresent notpresent
                                                                                                                                               423.0
          3 48.0
                              70.0
                                               1.005
                                                           4.0
                                                                  0.0
                                                                                normal
                                                                                         abnormal
                                                                                                            present notpresent
                                                                                                                                                117.0
          4 51.0
                              80.0
                                               1.010
                                                           2.0
                                                                  0.0
                                                                                normal
                                                                                           normal
                                                                                                         notpresent notpresent
                                                                                                                                               106.0
         5 rows × 25 columns
    # two method
    # radom sampling->higer null value
    # mean/mode-> lower null value
    def random_sampling(feature):
        random_sample = df[feature].dropna().sample(df[feature].isna().sum())
        random_sample.index = df[df[feature].isnull()].index
        df.loc[df[feature].isnull(), feature] = random_sample
    def impute_mode(feature):
        mode = df[feature].mode()[0]
        df[feature] = df[feature].fillna(mode)
    # random sampling for numerical value
    for col in num_cols:
        random_sampling(col)
    df[num_cols].isnull().sum()
     ₹
         blood_pressure
                                    0
         specific_gravity
                                    0
                                    0
         albumin
         sugar
                                    0
         blood_glucose_random
                                    0
         blood_urea
                                    0
```

```
white_blood_cell_count
                               0
     red_blood_cell_count
                               a
     dtype: int64
random_sampling('red_blood_cells')
random_sampling('pus_cell')
for col in cat_cols:
    impute_mode(col)
df[cat cols].isnull().sum()
```

serum_creatinine

packed_cell_volume

sodium

potassium

haemoglobin

0

0

0

0

0

```
→ red_blood_cells
     pus_cell
     pus_cell_clumps
                                0
     bacteria
                                0
     hypertension
     diabetes_mellitus
                                0
     {\tt coronary\_artery\_disease}
     appetite
     peda_edema
     aanemia
                                0
     class
     dtype: int64
# Feature Encoding
for col in cat_cols:
   print(f"{col} has {df[col].nunique()}")
→ red_blood_cells has 2
     pus_cell has 2
     pus_cell_clumps has 2
     bacteria has 2
     hypertension has 2
     diabetes_mellitus has 2
     coronary_artery_disease has 2
     appetite has 2
     peda_edema has 2
     aanemia has 2
     class has 2
# label_encoder
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for col in cat_cols:
   df[col] = le.fit_transform(df[col])
```

df.head()

		age	blood_pressure	specific_gravity	albumin	sugar	red_blood_cells	pus_cell	pus_cell_clumps	bacteria	blood_glucose_random	
	0	48.0	80.0	1.020	1.0	0.0	1	1	0	0	121.0	
	1	7.0	50.0	1.020	4.0	0.0	1	1	0	0	130.0	
	2	62.0	80.0	1.010	2.0	3.0	1	1	0	0	423.0	
	3	48.0	70.0	1.005	4.0	0.0	1	0	1	0	117.0	-
	4	51.0	80.0	1.010	2.0	0.0	1	1	0	0	106.0	

5 rows × 25 columns

```
0
     2
            0
     3
            a
     4
            0
     395
            1
     396
            1
     397
            1
     398
            1
     399
     Name: class, Length: 400, dtype: int64
from sklearn.model selection import train test split
X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, y, \text{test\_size} = 0.2, \text{random\_state} = 0)
# KNN
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_acc = accuracy_score(y_test, knn.predict(X_test))
print(f"Training Accuracy of KNN is {accuracy_score(y_train, knn.predict(X_train))}")
print(f"Testing \ Accuracy \ of \ KNN \ is \ \{accuracy\_score(y\_test, \ knn.predict(X\_test))\}")
print(f"Confusion Matrix of KNN is \n {confusion_matrix(y_test, knn.predict(X_test))}\n")
print(f"Classification Report of KNN is \n{classification\_report(y\_test, knn.predict(X\_test))}")
→ Training Accuracy of KNN is 0.78125
     Testing Accuracy of KNN is 0.7875
     Confusion Matrix of KNN is
      [[40 12]
      [ 5 23]]
     Classification Report of KNN is
                   precision
                                 recall f1-score
                                                     support
                         0.89
                                    0.77
                                              0.82
                0
                                                           52
                                              0.73
                                                           28
                                    0.82
                1
                         0.66
                                              0.79
                                                           80
         accuracy
        macro avg
                         0.77
                                    0.80
                                              0.78
                                                           80
                                              0.79
                                                           80
     weighted avg
                         0.81
                                    0.79
# Decision Tree
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
₹
      ▼ DecisionTreeClassifier
     DecisionTreeClassifier()
dtc_acc = accuracy_score(y_test, dtc.predict(X_test))
print(f"Training Accuracy of DTC is {accuracy_score(y_train, dtc.predict(X_train))}")
print(f"Testing Accuracy of DTC is {accuracy_score(y_test, dtc.predict(X_test))}")
print(f"Confusion Matrix of DTC is \n {confusion_matrix(y_test, dtc.predict(X_test))}\n")
print(f"Classification Report of DTC is \n{classification_report(y_test, dtc.predict(X_test))}")
→ Training Accuracy of DTC is 1.0
     Testing Accuracy of DTC is 0.975
     Confusion Matrix of DTC is
      [[51 1]
      [ 1 27]]
     Classification Report of DTC is
                    precision
                                 recall f1-score support
```

0.98

0.98

0

0.98

```
1
                        0.96
                                   0.96
                                             0.96
                                                         28
                                             0.97
                                                         80
         accuracy
                        0.97
                                   0.97
                                             0.97
                                                         80
        macro avg
                        0.97
                                   0.97
                                             0.97
                                                         80
     weighted avg
# Hyper Parameter Tuning
from sklearn.model_selection import GridSearchCV
GRID_PARAMETER = {
    'criterion':['gini','entropy'],
    'max_depth':[3,5,7,10],
    'splitter':['best','random'],
    'min_samples_leaf':[1,2,3,5,7],
    'min_samples_split':[1,2,3,5,7],
    'max_features':['auto', 'sqrt', 'log2']
}
grid_search_dtc = GridSearchCV(dtc, GRID_PARAMETER, cv=5, n_jobs=-1, verbose = 1)
grid_search_dtc.fit(X_train, y_train)
Fitting 5 folds for each of 1200 candidates, totalling 6000 fits
                  GridSearchCV
      ▶ estimator: DecisionTreeClassifier
            ▶ DecisionTreeClassifier
# best paramer and best score
print(grid_search_dtc.best_params_)
print(grid_search_dtc.best_score_)
    {'criterion': 'gini', 'max_depth': 7, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_samples_split': 7, 'splitter': 'best'}
     0.98125
dtc = grid_search_dtc.best_estimator_
dtc_acc = accuracy_score(y_test, dtc.predict(X_test))
print(f"Training Accuracy of DTC is {accuracy_score(y_train, dtc.predict(X_train))}")
print(f"Testing Accuracy of DTC is {accuracy_score(y_test, dtc.predict(X_test))}")
print(f"Confusion Matrix of DTC is \n {confusion_matrix(y_test, dtc.predict(X_test))}\n")
print(f"Classification Report of DTC is \n{classification_report(y_test, dtc.predict(X_test))}")
    Training Accuracy of DTC is 0.984375
     Testing Accuracy of DTC is 0.9625
     Confusion Matrix of DTC is
      [[49 3]
      [ 0 28]]
     Classification Report of DTC is
                   precision
                                recall f1-score
                                                    support
                0
                        1.00
                                   0.94
                                             0.97
                                                         52
                        0.90
                                             0.95
                                                         28
         accuracy
                                             96
                                                         ลล
                        0.95
                                   0.97
                                             0.96
                                                         80
        macro avg
     weighted avg
                        0.97
                                   0.96
                                             0.96
# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rand_clf = RandomForestClassifier(criterion = "gini", max_depth = 10, max_features="sqrt", min_samples_leaf= 1, min_samples_split= 7, n_esti
rand_clf.fit(X_train, y_train)
\rightarrow
                                 RandomForestClassifier
     RandomForestClassifier(max_depth=10, min_samples_split=7, n_estimators=400)
rand_clf_acc = accuracy_score(y_test, rand_clf.predict(X_test))
print(f"Training Accuracy of Random Forest is {accuracy_score(y_train, rand_clf.predict(X_train))}")
print(f"Testing \ Accuracy \ of \ Random \ Forest \ is \ \{accuracy\_score(y\_test, \ rand\_clf.predict(X\_test))\}")
```

```
print(f"Confusion Matrix of Random Forest is \n {confusion matrix(y test, rand clf.predict(X test))}\n")
print(f"Classification Report of Random Forest is \n{classification_report(y_test, rand_clf.predict(X_test))}")
Training Accuracy of Random Forest is 1.0
    Testing Accuracy of Random Forest is 0.9875
    Confusion Matrix of Random Forest is
     [[52 0]
     [ 1 27]]
    Classification Report of Random Forest is
                  precision
                              recall f1-score
                                                support
               0
                      0.98
                                1.00
                                         0.99
                                                     52
               1
                      1.00
                                0.96
                                         0.98
                                                     28
                                         0.99
                                                     80
        accuracy
                      0.99
                                0.98
                                         0.99
                                                     80
       macro avg
    weighted avg
                      0.99
                                0.99
                                         0.99
                                                     80
# XgBoost
from xgboost import XGBClassifier
xgb = XGBClassifier(objective="binary:logistic", learning_rate = 0.001, max_depth = 10, n_estimators = 100)
xgb.fit(X_train, y_train)
₹
                                   XGBClassifier
     XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
                  colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                  early_stopping_rounds=None, enable_categorical=False,
                  eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
                  grow_policy='depthwise', importance_type=None,
                  interaction_constraints='', learning_rate=0.001, max_bin=256,
                  max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
                  max_depth=10, max_leaves=0, min_child_weight=1, missing=nan,
                  monotone_constraints='()', n_estimators=100, n_jobs=0,
                  num_parallel_tree=1, predictor='auto', random_state=0, ...)
xgb_acc = accuracy_score(y_test, xgb.predict(X_test))
print(f"Training Accuracy of XGB is {accuracy_score(y_train, xgb.predict(X_train))}")
print(f"Testing Accuracy of XGB is {accuracy score(y test, xgb.predict(X test))}")
print(f"Classification Report of XGB is \n{classification_report(y_test, xgb.predict(X_test))}")
→ Training Accuracy of XGB is 0.98125
     Testing Accuracy of XGB is 0.9625
    Confusion Matrix of XGB is
     [[51 1]
     [ 2 26]]
    Classification Report of XGB is
                              recall f1-score
                  precision
                                                support
               0
                      0.96
                                0.98
                                         0.97
                                                     52
               1
                      0.96
                                0.93
                                         0.95
                                                     28
        accuracy
                                         0.96
                                                     80
                      0.96
                                0.95
                                         0.96
                                                     80
       macro avg
    weighted avg
                      0.96
                                0.96
                                         0.96
                                                     80
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train, y_train)
     ▼ LogisticRegression
     LogisticRegression()
lr_acc = accuracy_score(y_test, lr.predict(X_test))
print(f"Training\ Accuracy\ of\ LR\ is\ \{accuracy\_score(y\_train,\ lr.predict(X\_train))\}")
print(f"Testing Accuracy of LR is {accuracy_score(y_test, lr.predict(X_test))}")
print(f"Confusion Matrix of LR is \n {confusion_matrix(y_test, lr.predict(X_test))}\n")
```

```
→ Training Accuracy of LR is 0.934375
     Testing Accuracy of LR is 0.9375
     Confusion Matrix of LR is
      [[48 4]
      [ 1 27]]
     Classification Report of LR is
                   precision
                                 recall f1-score
                0
                        0.98
                                   0.92
                                             0.95
                                                          52
                1
                        0.87
                                   0.96
                                             0.92
                                                          28
                                             0.94
         accuracy
                        0.93
                                   0.94
                                             0.93
                                                          80
        macro avg
     weighted avg
                        0.94
                                   0.94
                                             0.94
                                                          80
# SVM
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
svm = SVC(probability=True)
parameter = {
    'gamma':[0.0001, 0.001, 0.01, 0.1],
    'C':[0.01, 0.05, 0.5, 0.1, 1, 10, 15, 20]
grid search = GridSearchCV(svm, parameter)
grid_search.fit(X_train, y_train)
₹
      ▶ GridSearchCV
       ▶ estimator: SVC
            ▶ SVC
print(grid_search.best_params_)
print(grid_search.best_score_)
→ {'C': 20, 'gamma': 0.0001}
     0.7375
svm = SVC(gamma = 0.0001, C = 15, probability=True)
svm.fit(X_train, y_train)
\overline{2}
                          SVC
     SVC(C=15, gamma=0.0001, probability=True)
svm_acc = accuracy_score(y_test, svm.predict(X_test))
print(f"Training Accuracy of SVC is {accuracy_score(y_train, svm.predict(X_train))}")
print(f"Testing Accuracy of SVC is {accuracy_score(y_test, svm.predict(X_test))}")
print(f"Confusion Matrix of SVC is \n {confusion_matrix(y_test, svm.predict(X_test))}\n")
print(f"Classification \ Report \ of \ SVC \ is \ \ \ \ (classification\_report(y\_test, \ svm.predict(X\_test)))")
    Training Accuracy of SVC is 0.990625
     Testing Accuracy of SVC is 0.7875
     Confusion Matrix of SVC is
      [[41 11]
      [ 6 22]]
     Classification Report of SVC is
                   precision
                                recall f1-score
                                                     support
                0
                        0.87
                                   0.79
                                             0.83
                                                          52
                1
                        0.67
                                   0.79
                                             0.72
                                                          28
                                             0.79
                                                          80
         accuracy
                        0.77
                                   0.79
                                                          80
        macro avg
                                             0.77
     weighted avg
                        0.80
                                   0.79
                                             0.79
                                                          80
```

[#] Gradient Boosting

 $from \ sklearn.ensemble \ import \ Gradient Boosting Classifier$

```
gbc = GradientBoostingClassifier()
PARAMETERS = {
    'loss': ['log_loss', 'exponential'],
    'learning_rate':[0.001, 0.1, 1, 10],
    'n_estimators':[100,150,180, 200]
grid_search_gbc = GridSearchCV(gbc, PARAMETERS, cv=5, n_jobs=-1, verbose= 1)
grid_search_gbc.fit(X_train, y_train)
Fitting 5 folds for each of 32 candidates, totalling 160 fits
                   GridSearchCV
      ▶ estimator: GradientBoostingClassifier
           ▶ GradientBoostingClassifier
          _____
print(grid_search_gbc.best_params_)
{'learning_rate': 1, 'loss': 'exponential', 'n_estimators': 100}
print(grid_search_gbc.best_score_)

→ 0.984375

gbc = GradientBoostingClassifier(learning_rate= 0.1, loss = 'log_loss', n_estimators = 100)
gbc.fit(X_train, y_train)
     ▼ GradientBoostingClassifier
     GradientBoostingClassifier()
gbc_acc = accuracy_score(y_test, gbc.predict(X_test))
print(f"Training Accuracy of GBC is {accuracy_score(y_train, gbc.predict(X_train))}")
print(f"Testing \ Accuracy \ of \ GBC \ is \ \{accuracy\_score(y\_test, \ gbc.predict(X\_test))\}")
print(f"Classification Report of GBC is \n{classification_report(y_test, gbc.predict(X_test))}")
    Training Accuracy of GBC is 1.0
     Testing Accuracy of GBC is 0.975
     Confusion Matrix of GBC is
     [[51 1]
     [ 1 27]]
     Classification Report of GBC is
                  precision
                              recall f1-score
                                0.98
               0
                       0.98
                                          0.98
                                                     52
                       0.96
                                0.96
                                          0.96
                                                     28
        accuracy
                                          0.97
                                                     80
       macro avg
                       0.97
                                0.97
                                          0.97
                                                     80
                       0.97
                                          0.97
                                                     80
     weighted avg
                                0.97
# Model Comparison
models = pd.DataFrame({
    'Model':['Logistic Regression', 'KNN', 'SVM', 'DT', 'Random Forest Classifier', 'XgBoost','Gradient Boosting'],
    'Score':[lr_acc, knn_acc, svm_acc, dtc_acc, rand_clf_acc, xgb_acc, gbc_acc]
})
models.sort_values(by='Score', ascending = False)
```

```
₹
                          Model Score
      4 Random Forest Classifier 0.9875
                Gradient Boosting 0.9750
      3
                            DT 0.9625
                        XgBoost 0.9625
      5
      0
              Logistic Regression 0.9375
      1
                           KNN 0.7875
      2
                           SVM 0.7875
import pickle
model = dtc
pickle.dump(model, open("kindey.pkl", 'wb'))
from sklearn import metrics
plt.figure(figsize=(8,5))
models = [
    'label': 'LR',
    'model': lr,
},
    'label': 'DT',
    'model': dtc,
},
    'label': 'SVM',
    'model': svm,
},
    'label': 'KNN',
    'model': knn,
},
{
    'label': 'XGBoost',
    'model': xgb,
},
    'label': 'RF',
    'model': rand_clf,
},
    'label': 'GBDT',
    'model': gbc,
}
for m in models:
    model = m['model']
    model.fit(X_train, y_train)
    y_pred=model.predict(X_test)
    fpr1, tpr1, thresholds = metrics.roc_curve(y_test, model.predict_proba(X_test)[:,1])
    auc = metrics.roc_auc_score(y_test,model.predict(X_test))
    plt.plot(fpr1, tpr1, label='%s - ROC (area = %0.2f)' % (m['label'], auc))
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1 - Specificity (False Positive Rate)', fontsize=12)
plt.ylabel('Sensitivity (True Positive Rate)', fontsize=12)
plt.title('ROC - Kidney Disease Prediction', fontsize=12)
plt.legend(loc="lower right", fontsize=12)
plt.savefig("roc_kidney.jpeg", format='jpeg', dpi=400, bbox_inches='tight')
plt.show()
```

```
<del>_</del>
                                                                                                  ROC - Kidney Disease Prediction
                         1.0
                       0.8
                       0.6
                  (True
                                                                                                                                                                      LR - ROC (area = 0.94)
                       0.4
                                                                                                                                                                      DT - ROC (area = 0.98)
 from sklearn import metrics
 import numpy as np
 import matplotlib.pyplot as plt
models = [
 {
             'label': 'LR',
              'model': lr,
},
             'label': 'DT',
             'model': dtc,
},
             'label': 'SVM',
              'model': svm,
},
              'label': 'KNN',
              'model': knn,
},
 {
              'label': 'XGBoost',
              'model': xgb,
},
 {
             'label': 'RF',
              'model': rand_clf,
},
             'label': 'GBDT',
             'model': gbc,
}
 ]
means_roc = []
means\_accuracy = [100*round(lr\_acc,4), 100*round(dtc\_acc,4), 100*round(svm\_acc,4), 100*round(knn\_acc,4), 100*round(xgb\_acc,4), 100
                                                       100*round(rand_clf_acc,4), 100*round(gbc_acc,4)]
 for m in models:
            model = m['model']
            model.fit(X_train, y_train)
            y_pred=model.predict(X_test)
            fpr1, tpr1, thresholds = metrics.roc_curve(y_test, model.predict_proba(X_test)[:,1])
            \verb"auc = metrics.roc_auc_score(y_test,model.predict(X_test))"
            auc = 100*round(auc,4)
            means_roc.append(auc)
 print(means_accuracy)
print(means_roc)
n_groups = 7
means_accuracy = tuple(means_accuracy)
means_roc = tuple(means_roc)
fig, ax = plt.subplots(figsize=(8,5))
```