■ DOWNLOAD THE DATASET

■IMPORT THE LIBRARIES

```
In []: # Importing Libraries:
    import pandas as pd
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    import plotlib.express as px
    import plotly.express as px
    import warnings
    warnings.filterwarnings('ignore') #never print matching warnings
    plt.style.use('fivethirtyeight') #to replicate the styles from FiveThirtyEight.com.
    pd.set_option('display.max_columns',26)
In []: from eacels calch import files
```

from google.colab import files
files.upload()

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable. Saving kidney_disease2.csv to kidney_disease2.csv

w, normal, notpresent, notpres

READ THE DATASET

```
In [ ]: df = pd.read_csv("kidney_disease2.csv")
In [ ]: df.head()
        id age bp sg al su rbc
                                                      ba bgr bu sc sod pot hemo pcv wc rc htn dm cad appet pe ane classific
                                      рс
                                             рсс
      0 0 48.0 80.0 1.020 1.0 0.0 NaN
                                    normal notpresent notpresent 121.0 36.0 1.2 NaN NaN
                                                                             15.4 44 7800 5.2 yes yes
      1 1 7.0 50.0 1.020 4.0 0.0 NaN normal notpresent notpresent NaN 18.0 0.8 NaN NaN 11.3 38 6000 NaN no no no good no no
           62.0 80.0 1.010 2.0 3.0 normal
                                   normal notpresent notpresent 423.0 53.0 1.8 NaN NaN
                                                                                  31 7500 NaN
      3 3 48.0 70.0 1.005 4.0 0.0 normal abnormal present notpresent 117.0 56.0 3.8 111.0 2.5 11.2 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 26.0 1.4 NaN NaN 11.6 35 7300 4.6 no no no good no no
       #making columns meaningful
       In [ ]: df.head()
```

```
0 0 48.0
                                 80.0
                                                1.020
                                                             1.0
                                                                    0.0
                                                                                   NaN
                                                                                          normal
                                                                                                          notpresent notpresent
                                                                                                                                                  121.0
                                                                                                                                                               36.0
           1 1 7.0
                                 50.0
                                                1.020
                                                            4.0
                                                                   0.0
                                                                                  NaN normal
                                                                                                                                                  NaN
                                                                                                                                                               18.0
           2 2 62.0
                                 80.0
                                                 1.010
                                                             2.0
                                                                    3.0
                                                                                 normal normal
                                                                                                          notpresent notpresent
                                                                                                                                                  423.0
                                                                                                                                                               53.0
                             70.0 1.005 4.0 0.0 normal abnormal
                                                                                                         present notpresent
           4 4 51.0
                                 80.0
                                        1.010 2.0 0.0
                                                                                 normal normal
                                                                                                          notpresent notpresent
                                                                                                                                                  106.0
                                                                                                                                                               26.0
          4
           ■Understanding Data Type And Summary Of Features
 In [ ]: df.info()
           RangeIndex: 400 entries, 0 to 399
           Data columns (total 26 columns):

# Column Non-Null Count Dtype
                                             400 non-null
391 non-null
388 non-null
353 non-null
                                                                int64
float64
float64
float64
                 Blood_Pressure
Specific_Gravity
Albumin
                                              354 non-null
                                                                 float64
                Albumin
Sugar
Red_Blood_Cells
Pus_Cells
Puss_Cell_Clumps
Bacteria
Rlood_Gulcose_Random
                                              351 non-null
                                                                 float64
                                                                object
object
object
object
float64
                                              248 non-null
                                              335 non-null
396 non-null
396 non-null
                Blood_Urea
                                              381 non-null
           12
                Serum Creatinine
                                              383 non-null
                                                                 float64
                                              313 non-null
           13
                Sodium
                                                                 float64
           14
                Potassium
                                              312 non-null
                                                                 float64
                Haemoglobin
Packed_Cell_Volume
White_Blood_Cell_Count
           15
                                              348 non-null
                                                                 float64
                                             330 non-null
295 non-null
                                                                 object
                Red_Blood_Cell_Count
Hypertension
Diabetes_Mellitus
                                                                 object
object
           18
                                              270 non-null
                                              398 non-null
           20
                                              398 non-null
                                                                 object
           21
                Coronary_Artery_Disease
                                              398 non-null
                                                                 object
           22
                Appetite
                                              399 non-null
                                                                 object
                                                                 object
object
           23
                Peda Edema
                                              399 non-null
                Aanemia
                                              399 non-null
           25 clas s
                                              400 non-null
                                                                 object
          dtypes: \bar{\text{float64(11)}}, int64(1), object(14)
          memory usage: 81.4+ KB
In [ ]: df.describe()
                         id
Out[ ]:
                                    Age Blood_Pressure Specific_Gravity
                                                                                            Sugar Blood_Gulcose_Random Blood_Urea Serum_Creatinine
                                                                             Albumin
          count 400.000000 391.000000
                                              388.000000
                                                               353.000000 354.000000 351.000000
                                                                                                                356.000000 381.000000
                                                                                                                                               383.000000 3
                                                                                                                                          3.072454 1
          mean 199.500000 51.483376 76.469072
                                                           1.017408 1.016949 0.450142
                                                                                                               148.036517 57.425722
            std 115.614301 17.169714
                                              13.683637
                                                                0.005717
                                                                             1.352679
                                                                                        1.099191
                                                                                                                79.281714 50.503006
         min 0.000000 2.000000 50.000000 1.005000 0.000000 0.000000
                                                                                         22.000000 1.500000
                                                                                                                            0.400000 4.500000 2.500000
         25% 99.750000 42.000000
                                        70.000000
                                                        1.010000 0.000000
                                                                            0.000000
                                                                                                 99 000000 27 000000
                                                                                                                              0.900000 135.000000
                                                                                                                                                  3.800000
         50% 199.500000 55.000000 80.000000
                                                       1.020000 0.000000 0.000000
                                                                                                121.000000 42.000000
                                                                                                                             1.300000 138.000000 4.400000
         75% 299.250000 64.500000 80.000000 1.020000 2.000000 0.000000
                                                                                               163.000000 66.000000
                                                                                                                             2.800000 142.000000 4.900000

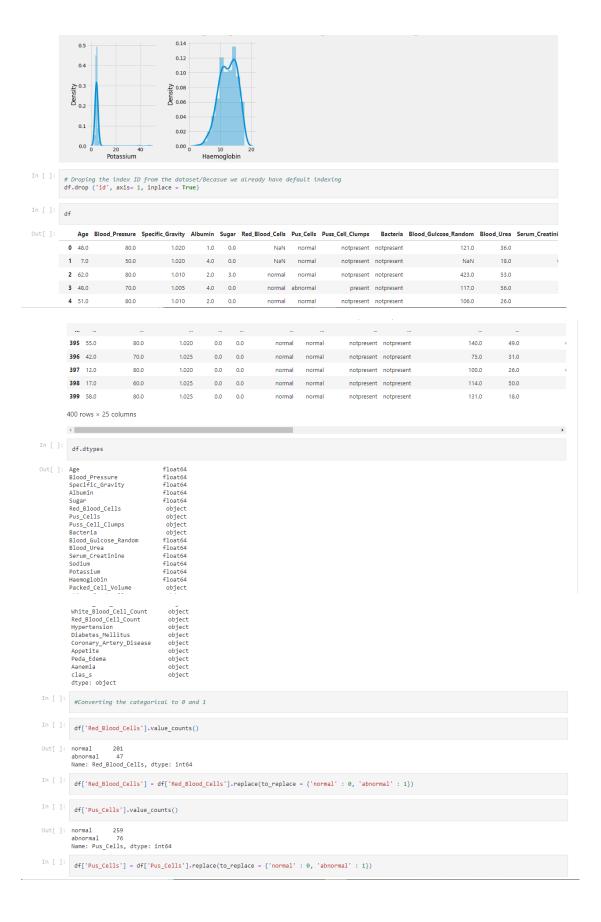
        max
        399.000000
        90.000000
        180.000000
        1.025000
        5.000000
        5.000000

                                                                                               490.000000 391.000000
                                                                                                                            76,000000 163,000000 47,000000
       4
        SOME VISUALISATIONS OVER DATA
        number_columns = [col for col in df.columns if df[col].dtype != 'object']
         plt.figure(figsize = (20, 15))
plotnumber = 1
         for column in number_columns:
             if plotnumber <= 14:

ax = plt.subplot(3, 5, plotnumber)

sns.distplot(df[column])
                 plt.xlabel(column)
plotnumber += 1
         plt.tight_layout()
plt.show()
```

id Age Blood_Pressure Specific_Gravity Albumin Sugar Red_Blood_Cells Pus_Cells Puss_Cell_Clumps Bacteria Blood_Gulcose_Random Blood_Urea Serum_Creati



```
In [ ]: df['Puss_Cell_Clumps'].value_counts()
Out[ ]: notpresent 354
          present 42
Name: Puss_Cell_Clumps, dtype: int64
In [ ]: df['Puss_Cell_Clumps'] = df['Puss_Cell_Clumps'].replace(to_replace = {'notpresent':0,'present':1})
In [ ]: df['Hypertension'].value_counts()
Out[]: no 251
yes 147
Name: Hypertension, dtype: int64
In [ ]:  df['Hypertension'] = df['Hypertension'] \cdot replace(to_replace = \{'yes' : 1, 'no' : 0\}) 
In [ ]: df['Diabetes_Mellitus'].value_counts()
Out[]: no 258

yes 134

\tno 3

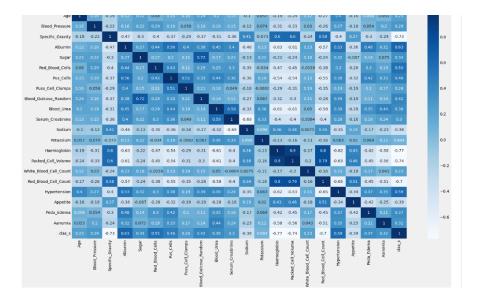
\tyes 2

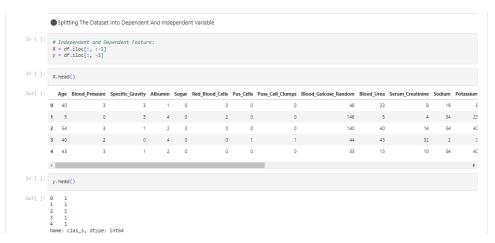
yes 1

Name: Diabetes_Mellitus, dtype: int64
  In [ ]: df['Coronary_Artery_Disease'].value_counts()
 Out[]: no 362
yes 34
\tno 2
Name: Coronary_Artery_Disease, dtype: int64
  In [ ]: df['Coronary_Artery_Disease'] = df['Coronary_Artery_Disease'].replace(to_replace = {'\tno':'no'})
 In [ ]: df['Appetite'].unique()
  Out[ ]: array(['good', 'poor', nan], dtype=object)
  In [ ]: df['Appetite'] = df['Appetite'].replace(to_replace={'good':1,'poor':0,'no':np.nan})
 In [ ]: df['Peda_Edema'].value_counts()
  Out[ ]: no 323
yes 76
Name: Peda_Edema, dtype: int64
  In [ ]: df['Peda_Edema'] = df['Peda_Edema'].replace(to_replace = {'yes' : 1, 'no' : 0})
  In [ ]: df['Aanemia'].value_counts()
Out[]: no 339
yes 60
Name: Aanemia, dtype: int64
In [ ]: df['Aanemia'] = df['Aanemia'].replace(to_replace = {'yes' : 1, 'no' : 0})
           #TARGET COLUMN
           df['clas_s'].value_counts()
Out[]: ckd 248
notckd 150
ckd\t 2
Name: clas_s, dtype: int64
In [ ]: df['clas_s'] = df['clas_s'].replace(to_replace={'ckd\t':'ckd'})
In [ ]: df["clas_s"] = [1 if i == "ckd" else 0 for i in df["clas_s"]]
          # Gonna remove the bacteria column , nothing is present in the dataset df.drop ('Bacteria', axis= 1, inplace = True)
In [ ]: df.info() #Converting PCV, WBCC, RBCC ( Objects to numberic)
```

■ Handling The Missing Values

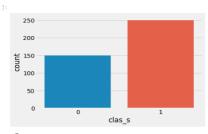
```
In [ ]: df.isnull().sum().sort_values(ascending=False)
 Out[]: Red_Blood_Cells
           Red_Blood_Cell_Count
White_Blood_Cell_Count
Potassium
                                              131
           Sodium
Packed_Cell_Volume
Pus_Cells
Haemoglobin
            Sugar
Specific_Gravity
            Albumin
Blood_Gulcose_Random
           Blood_Urea
Serum_Creatinine
Blood_Pressure
                                               19
17
            Age
Puss_Cell_Clumps
           Hypertension
Diabetes_Mellitus
Coronary_Artery_Disease
Appetite
           Peda_Edema
Aanemia
           Aanemia
           clas_s
dtype: int64
In [ ]:
    cat_features = ['Red_Blood_Cells','Pus_Cells','Pus_Cell_clumps',
    'Hypertension','Diabetes_Mellitus','Coronary_Artery_Disease',
    'Appetite','Peda_Edema','Aanemia']
In [ ]:
    for feature in cat_features:
        df[feature] = df[feature].fillna(df[feature].mode())
In [ ]: for feature in num_features:
    df[feature] = df[feature].fillna(df[feature].mode())
           Checking the total number of null values
In [ ]: df.columns.isnull().sum()
Out[ ]: 0
```





THERE ARE NO FEATURES ABOVE 0.95 MULTI-COLLINEARITY SO NO DROPPING

```
In []: # Target feature:
# Show the counts of observations using bars.
sns.countplot(df['clas_s'])
```



■ LABEL ENCODING

```
In [ ]: from sklearn.preprocessing import LabelEncoder
lab_enc = LabelEncoder()
for i in df:
    df[i] = lab_enc.fit_transform(df[i])
```

■ Splitting The Dataset Into Dependent And Independent Variable

```
In [ ]: # Independent and Dependent Feature:
    X = df.iloc[:, :-1]
    y = df.iloc[:, -1]
```

In []: X.head()

Out[]:		Age	Blood_Pressure	Specific_Gravity	Albumin	Sugar	Red_Blood_Cells	Pus_Cells	Puss_Cell_Clumps	Blood_Gulcose_Random	Blood_Urea	Serum_Creatinine	Sodium	Potassium	
	0	40	3	3	1	0	0	0	0	48	23	8	19	8	
	1	5	0	3	4	0	2	0	0	146	5	4	34	23	
	2	54	3	1	2	3	0	0	0	140	40	14	34	40	
	3	40	2	0	4	0	0	1	1	44	43	32	2	C	
	4	43	3	1	2	0	0	0	0	33	13	10	34	40	
	4													+	

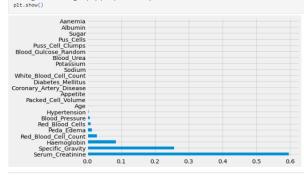
In []: y.head()

Out[]: 0 1 1 1 2 1

Name: clas_s, dtype: int64

● CHECKING FEATURE IMPORTANCE

$$\label{eq:pit-figsize} \begin{split} & \text{plt-figsize-}(8,6)) \\ & \text{ranked_features-pd.Series(model.feature_importances_,index-X.columns)} \\ & \text{ranked_features.nlargest(24).plot(kind='barh')} \\ & \text{plt.show()} \end{split}$$



In []: ranked_features.nlargest(8).index

In []: X = df[['Haemoglobin', 'Specific_Gravity', 'Red_Blood_Cell_Count', 'Albumin', 'Blood_Drea', 'Blood_Pressure', 'Blood_Gulcose_Random', 'Serum_Creatinin X.head()

Out[]: Haemoglobin Specific_Gravity Red_Blood_Cell_Count Albumin Blood_Urea Blood_Pressure Blood_Gulcose_Random Serum_Creatinine
 0
 90
 3
 30
 1
 23
 3
 48
 6

 1
 49
 3
 45
 4
 5
 0
 146
 4
 2 32 1 45 2 40 3 140 14 3 48 0 17 4 43 2 44 32

● SPLITTING THE DATASET INTO TRAINSET AND SPLIT TEST

In []: # Train Test Split:
 from sklearn.model_selection import train_test_split
 X_train_X_test,y_train,y_test = train_test_split(X,y, test_size=0.3, random_state=33)
 print(X_train.shape)
 print(X_train.shape)

```
■BUILDING THE MODEL
In [ ]: # Importing Performance Metrics: from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
In [ ]:
    # DecisionTreeClassifier:
    from sklearn.tree import DecisionTreeClassifier
    model = DecisionTreeClassifier()
    model = model.fit(X_train,y_train)
          TESTING THE MODEL
●MODEL EVALUATION
In [ ]:
    y_pred = model.predict(X_test)
    # Performance:
    print('Accuracy:', accuracy_score(y_test,y_pred))
    print('Confusion Natrix(', test,y_pred))
    print('Classification Natrix(')
    print('classification Natrix(')
    print('classification Natrix(')
    print('classification Natrix(')
    print('classification Natrix(')
    print(')
          print(classification_report(y_test,y_pred))
         SAVING THE MODEL
■ LISTING THE FILES
In [ ]: 1s
           _CKD_NEW2.pk1 'processed_kidney_disease 2.csv' sample_data/
kidney_disease2.csv processed_kidney_disease2.csv
          ● DOWNLOADING THE FILES
 In [ ]: files.download('_CKD_NEW2.pkl') # Downloading the pickle file --> Python object hierarchy is converted into a byte stream
```