

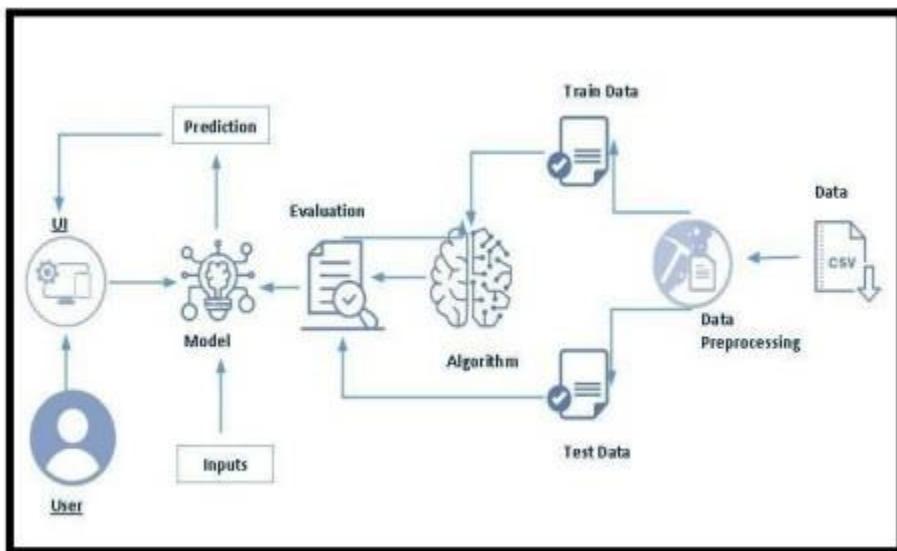
# EARLY PREDICTION FOR CHRONIC KIDNEY DISEASE DETECTION:A PROGRESSIVE APPROACH TO HEALTH MANAGEMENT

## OVERVIEW:

Chronic Kidney Disease (CKD) is a major medical problem and can be cured if treated in the early stages. Usually, people are not aware that medical tests we take for different purposes could contain valuable information concerning kidney diseases. Consequently, attributes of various medical tests are investigated to distinguish which attributes may contain helpful information about the disease. The information says that it helps us to measure the severity of the problem, the predicted survival of the patient after the illness, the pattern of the disease and work for curing the disease.

In todays world as we know most of the people are facing so many disease and as this can be cured if we treat people in early stages this project can use a pretrained model to predict the Chronic Kidney Disease which can help in treatments of peoples who are suffer from this disease.

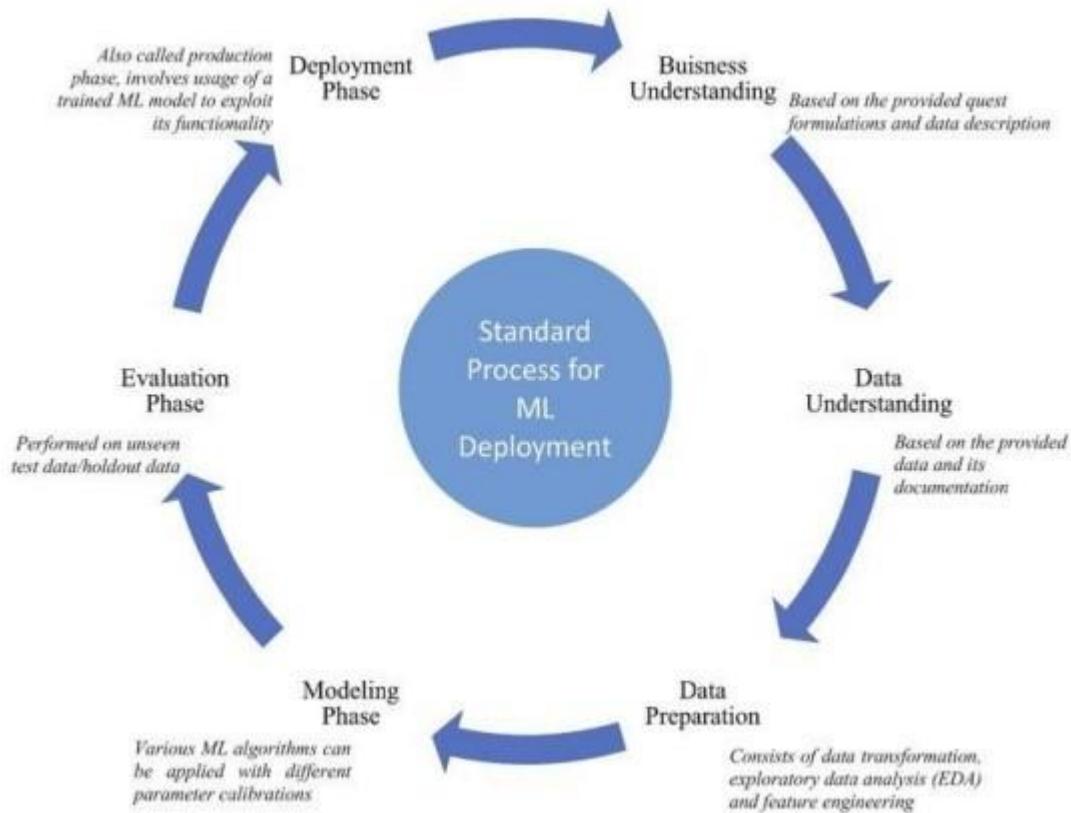
## TECHNICAL ARCHITECTURE:



## TECHNICAL ABOUT THE PROJECT:

Machine learning is merely based on predictions made based on experience. It enables machines to make data-driven decisions, which is more efficient than explicitly programming to carry out certain tasks. These algorithms are designed

in a fashion that gives exposure to new data that can help organisations learn and improve their strategies.



#### A PROJECT DESCRIPTION:

Kidney diseases (acute and chronic) are an important public health problem, and chronic kidney disease (CKD) is a noncommunicable disease of global significance. CKD is defined by the presence of kidney damage or reduced kidney function for a period of at least 3 months, with implications for health. The level of disease severity has been used to classify CKD into various stages, from persistent kidney damage only with preserved kidney function (estimated glomerular filtration rate (eGFR) >90ml/min/1.73m<sup>2</sup>; stage 1) to persistent kidney damage accompanied by mild reduction in kidney function (eGFR 60-90; stage 2) to moderate to severe reduction in kidney function (eGFR 30-60; stage 3, and eGFR 15-30; stage 4). Stage 5 (eGFR <15) refers to the advanced stage of CKD also termed “kidney failure,” which can progress to end-stage kidney disease (ESKD), where dialysis therapy or kidney transplantation is essential to maintain life.

CDC's Kidney Disease Surveillance System is the first surveillance system of its

kind developed in the United States to focus on tracking kidney disease prior to ESKD. It has a serious responsibility for serving as a timely and comprehensive surveillance and information system. Findings from this system highlighted on the project's website are intended to raise awareness of multiple facets of kidney disease (prevalence and incidence, risk factors, awareness, quality of care, health outcomes, and its social determinants of health), to spur individuals, communities, policymakers, researchers, clinicians, and health systems, to bring about incremental and sustainable improvements to reduce the impact of this often-neglected non-communicable disease.

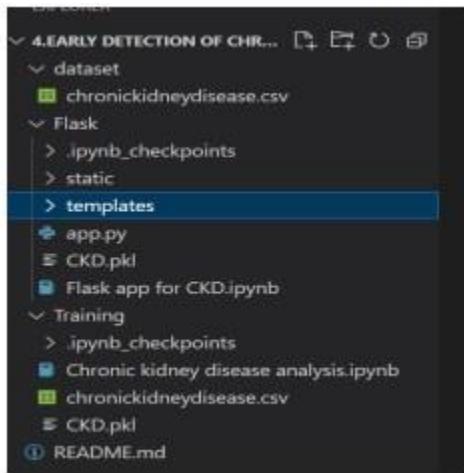
## PROJECT FLOW:

- User interacts with the UI to enter the input.
  - Entered input is analysed by the model which is integrated.
  - Once model analyses the input the prediction is showcased on the UI
- To accomplish this, we have to complete all the activities listed below,
- Define Problem / Problem Understanding
    - Specify the business problem
    - Business requirements
    - Literature Survey
    - Social or Business Impact.
  - Data Collection & Preparation
    - Collect the dataset
    - Data Preparation
  - Exploratory Data Analysis
    - Descriptive statistical
    - Visual Analysis
  - Model Building
    - Training the model in multiple algorithms

- Testing the model
- Performance Testing & Evaluate the results
  - Testing model with multiple evaluation metrics
  - Evaluate the results
- Model Deployment
  - Save the best model
  - Integrate with Web Framework
- Project Demonstration & Documentation
  - Record explanation Video for project end to end solution
  - Project Documentation-Step by step project development procedure

## PROJECT STRUCTURE:

Create the Project folder which contains files as shown below



- We are building a flask application which needs HTML pages stored in the templates folder

## PURPOSE:

There are limited data to describe academic achievement outcomes for children with mild to moderate pediatric chronic kidney disease (CKD). The objective of this study was to describe the prevalence of low academic achievement in patients with mild to moderate CKD.

#### Design, Setting, Participants, and Measurements:

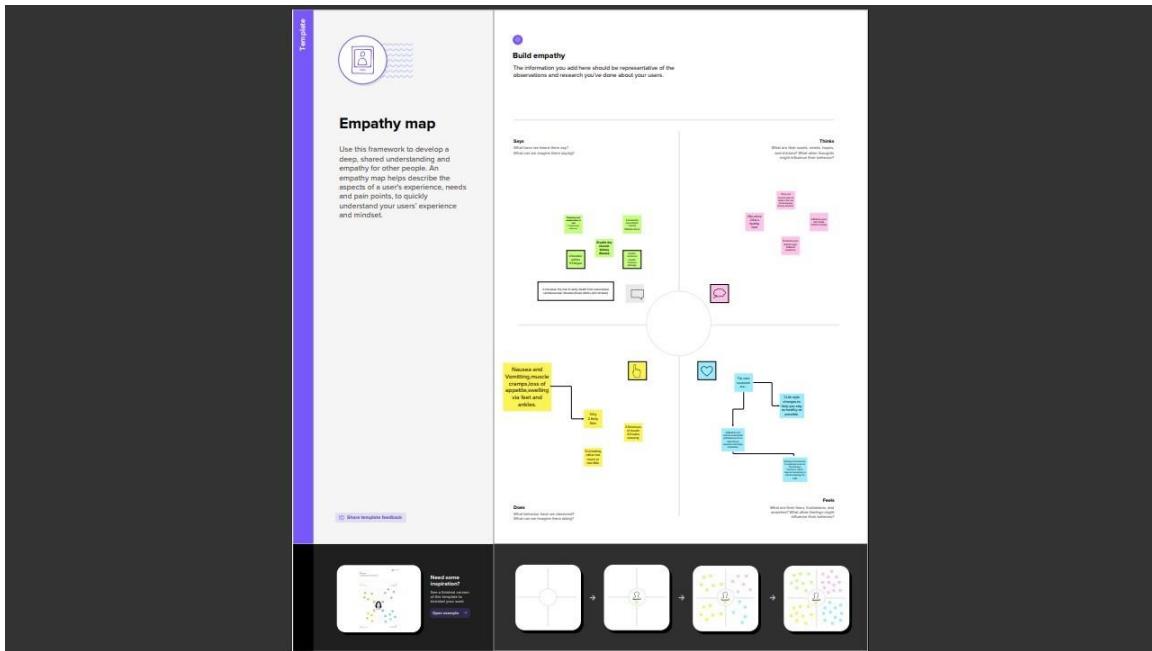
Wechsler Individual Achievement Test, Second Edition, Abbreviated (WIAT-II-A) data were collected at entry into the Chronic Kidney Disease in Children (CKiD) study. Achievement in basic reading, spelling, mathematics, and total achievement was evaluated with a focus on the effects of comorbid CKD-related variables, neurocognitive, and school-based characteristics on academic achievement.

The physical sequelae of pediatric chronic kidney disease (CKD) are well characterized [1]. Data support the parallel presence of subtle neurocognitive deficits in even mild to moderate pediatric CKD. Specifically, cognitive executive function, the neurocognitive ability to plan and make complex decisions, may be impaired in CKD [2]. As with executive function, behavioral concerns are reported by parents of children with CKD [3]. Although the specific mechanisms of neurocognitive and behavioral dysfunction associated with CKD are not fully understood, there is evidence to suggest that decline in renal function, early age of onset, and proteinuria increase the risk for neurocognitive and behavioral shortfalls even before the disease advances to the need for dialysis or transplantation [4].

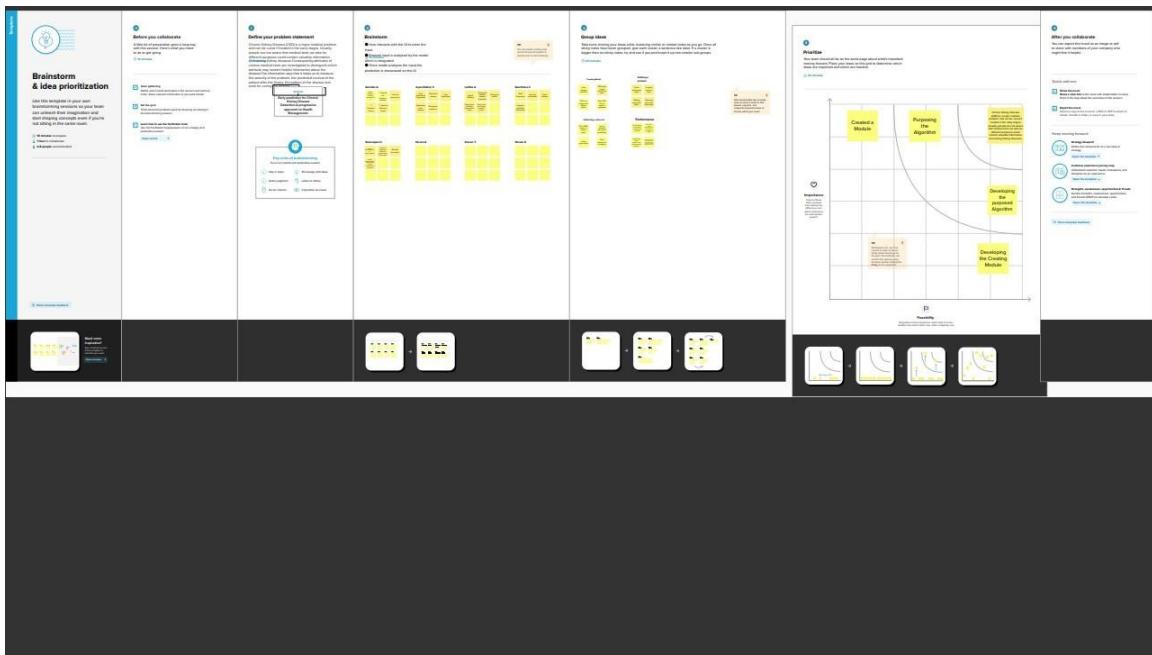
#### Problem Definition And Design Thinking :

Machine learning has become an increasingly popular tool in recent years ,given its ability to automatically detect patterns in data and make predictions about future events .this can be extremely useful for making decisions in a wide range of domains,from financial trading to medical diagnoses Empathy Map

#### 2.1 EMPATHY MAP:



## 2.2 Ideation and Brainstorming Map:



**RESULT:**

The image consists of three vertically stacked screenshots of a web application titled "Chronic Kidney Disease: A Machine Learning Web App built with Flask".

- Screenshot 1:** Shows the input form. It contains several dropdown menus with the following values:
  - Age: 1
  - Gender: Male
  - Race: Black
  - Diabetes: Yes
  - Smoking: Yes
  - Blood Pressure: Yes
  - Glucose: Yes
  - Albumin: Yes
  - Urea: Yes
  - Creatinine: Yes
 A "Predict" button is located at the bottom right.
- Screenshot 2:** Shows the prediction result. The text "Prediction: Great! You DON'T have Chronic Kidney Disease" is displayed in green. Below it is a colorful image of the Minions from the movie Despicable Me, with the text "IT'S TIME TO PARTYYYYY!" overlaid.
- Screenshot 3:** A blank browser window with the title bar "Chronic Kidney Disease" and the URL "127.0.0.1:5000/predict".

#### ADVANTAGE:

The number of patients on renal replacement therapy has doubled every decade since 1980, and prevalence of chronic kidney disease (CKD) in the early stages is also markedly increased.

In addition, CKD is a significant risk factor for cardiovascular morbidity and mortality. The only effective approach to this problem is prevention and early detection of CKD. In recent years, screening studies have been carried out in several countries

The findings have defined the scope of the problem and indicated which population

groups are at risk of developing CKD. The most numerous are patients with hypertension and diabetes. Also, these studies have indicated that screening should include measurement of serum creatinine for eGFR as well as urine albumin.

Early detection of CKD allows proper management that could slow down CKD progression, prevent cardiovascular and other comorbidities and enable timely initiation of dialysis. Screening for CKD could be best managed by partnership between primary care physicians and nephrologists. It is necessary to educate primary care physicians about CKD, its risk factors and associated co-morbidities.

Although multiple benefits of screening for CKD are doubtless, the results obtained by screening should be interpreted with caution, bearing in mind that screening detects only markers of kidney disease but not the disease itself.

#### DISADVANTAGES:

Having CKD increases the chances of having heart disease and stroke. Managing high blood pressure, blood sugar, and cholesterol levels—all factors that increase the risk for heart disease and stroke—is very important for people with CKD.

Anemia. This happens when your kidneys don't make enough erythropoietin (EPO), which affects their ability to make red blood cells. ...

Bone weakness. ...

Fluid retention. ...

Gout. ...

Heart disease. ...

High blood pressure (hypertension). ...

Hyperkalemia. ...

Metabolic acidosis.

#### APPLICATIONS:

The main treatments are: lifestyle changes – to help you stay as healthy as possible. medicine – to control associated problems, such as high blood pressure and high cholesterol. dialysis – treatment to replicate some of the kidney's functions, which may be necessary in advanced (stage 5) CKD.

Lifestyle changes

The following lifestyle measures are usually recommended for people with kidney disease:

stop smoking if you

smoke eat a healthy,

balanced diet

Medicine

There's no medicine specifically for CKD, but medicine can help control many of the problems that cause the condition and the complications that can happen as a result of it.

You may need to take medicine to treat or prevent the different problems caused by CKD.

High blood pressure

Good control of blood pressure is vital to protect the kidneys.

People with kidney disease should usually aim to get their blood pressure down to below

140/90mmHg, but you should aim to get it down to below 130/80mmHg if you also have diabetes

Most people know that a major function of the kidneys is to remove waste products and excess fluid from the body. These waste products and excess fluid are removed through the urine. The production of urine involves highly complex steps of excretion and re-absorption.

Tests of renal function can be used to assess overall renal function by direct measurement or estimation of the glomerular filtration rate. Estimation of the GFR is utilized to determine the presence of renal impairment.18-Jul-2022

The critical regulation of the body's salt, potassium and acid content is performed by the kidneys. The kidneys also produce hormones that affect the function of other organs. For example, a hormone produced by the kidneys stimulates red blood cell production

Nephrology (from Greek nephros "kidney", combined with the suffix -logy, "the study of") is a specialty of adult internal medicine and pediatric medicine that concerns the study of the kidneys, specifically normal kidney function (renal physiology) and kidney disease (renal pathophysiology), the preservation of kidney.

Dialysis is a treatment for people whose kidneys are failing. When you have kidney failure, your kidneys don't filter blood the way they should. As a result, wastes and toxins build up in your bloodstream. Dialysis does the work of your kidneys, removing waste products and excess fluid from the blood.

## CONCLUSION:

Chronic renal failure represents a critical period in the evolution of chronic renal disease and is associated with complications and comorbidities that begin early in the course of the disease. These conditions are initially subclinical but progress relentlessly

and may eventually become symptomatic and irreversible. Early in the course of chronic renal failure, these conditions are amenable to interventions with relatively simple treatments that have the potential to prevent adverse outcomes. Fig Fig33 summarises strategies for effective management of chronic renal disease. By acknowledging these facts, we have an excellent opportunity to change the paradigm of management of chronic renal failure and improve patient outcomes.

The perception of advantages and disadvantages of APD differed between patients undergoing APD and CAPD; the former focus on the frequency of bag exchange, whereas the latter focused the size of device.

#### FUTURESCOPE:

Imaging: assessing nephron number as a determinant of kidney disease and kidney fibrosis

Imaging techniques have the advantage of being non-invasive and, thus, may be safely repeated to evaluate changes, providing information for both kidneys and potentially combining functional with morphological information. The most interesting advances relate to estimation of nephron number, overall kidney functions, fibrosis and new functional magnetic resonance imaging (MRI), as well as ultrasound techniques such as diffusion-weighted MRI (DWI or DW-MRI), blood oxygenation level-dependent MRI (BOLD-MRI), perfusion MRI, hyperpolarized (HP) carbon 13 MRI (13C MRI) and contrast-enhanced ultrasound (CEUS).

CFE-MRI uses ferritin filled with an iron oxide future treatments for kidney disease

Novel therapeutic alternatives for ESRD include wearable artificial kidneys, xenotransplantation, stem cell-based therapy, and bioengineered and bio-artificial kidneys. Of note, one of the main objectives of these novel therapeutic approaches should be to maintain patients at home and to avoid dialysis.

#### APPENDIX:

copys of Last chronic kidney disease\_task 2 to 5

```
import pandas as pd
import numpy as np
from collections import Counter as c
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as mno
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
import pickle

[ ] from google.colab import files
uploaded = files.upload()

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving kidney_disease.csv to kidney_disease.csv

[ ] data=pd.read_csv("kidney_disease.csv")
data.head()
```

id age bp sg al su rbc pc pcc ba ... pcv wc rc htn dm cad appet pe ane classification

File | Home

copys of Last chronic kidney disease\_task 2 to 5

```
data=pd.read_csv("kidney_disease.csv")
data.head()
```

	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 x 26 columns

```
data.tail()
```

	id	age	bp	sg	al	su	rbc	pc	pcc	ba	...	pcv	wc	rc	htn	dm	cad	appet	pe	ane	classification
395	395	55.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	47	6700	4.9	no	no	no	good	no	no	notckd
396	396	42.0	70.0	1.025	0.0	0.0	normal	normal	notpresent	notpresent	...	54	7800	6.2	no	no	no	good	no	no	notckd
397	397	12.0	80.0	1.020	0.0	0.0	normal	normal	notpresent	notpresent	...	49	6600	5.4	no	no	no	good	no	no	notckd

copys of Last chronic kidney disease\_task 2 to 5

```
[ ] data.head(10)
   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 c
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 c
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 c
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 c
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 c
5 5 60.0 90.0 1.015 3.0 0.0 NaN NaN notpresent notpresent ... 39 7800 4.4 yes yes no good yes no c
6 6 68.0 70.0 1.010 0.0 0.0 NaN normal notpresent notpresent ... 36 NaN NaN no no no good no no c
7 7 24.0 NaN 1.015 2.0 4.0 normal abnormal notpresent notpresent ... 44 6900 5 no yes no good yes no c
8 8 52.0 100.0 1.015 3.0 0.0 normal abnormal present notpresent ... 33 9600 4.0 yes yes no good no yes c
9 9 53.0 90.0 1.020 2.0 0.0 abnormal abnormal present notpresent ... 29 12100 3.7 yes yes no poor no yes c
10 rows x 26 columns
```

[ ] data.drop(["id"],axis=1,inplace=True)

copys of Last chronic kidney disease\_task 2 to 5

```
[ ] data.drop(["id"],axis=1,inplace=True)

[ ] data.columns
Index(['age', 'bp', 'sg', 'al', 'su', 'rbc', 'pc', 'pcc', 'ba', 'bgn', 'bu',
       'sc', 'sod', 'pot', 'hemo', 'pcv', 'wc', 'rc', 'htn', 'dm', 'cad',
       'appet', 'pe', 'ane', 'classification'],
      dtype='object')

[ ] data.columns
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',
       'hemoglobin', 'packed_cell_volume', 'white_blood_cell_count', 'red_blood_cell_count',
       'hypertension', 'diabetesmellitus', 'coronary_artery_disease', 'appetite',
       'pedal_edema', 'anemia', 'class'])
```

copies of Last chronic kidney disease\_task 2 to 5

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 25 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   age              391 non-null    float64
 1   blood_pressure   388 non-null    float64
 2   specific_gravity 353 non-null    float64
 3   albumin          354 non-null    float64
 4   sugar             351 non-null    float64
 5   red_blood_cells  248 non-null    object  
 6   pus_cell          335 non-null    object  
 7   pus_cell_clumps  396 non-null    object  
 8   bacteria          396 non-null    object  
 9   blood_glucose_random 356 non-null    float64
 10  blood_urea        381 non-null    float64
 11  serum_creatinine 383 non-null    float64
 12  sodium            313 non-null    float64
 13  potassium         312 non-null    float64
 14  hemoglobin        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  
 18  hypertension       398 non-null    object  
 19  diabetesmellitus  200 non-null    object 
```

copies of Last chronic kidney disease\_task 2 to 5

```
age          True
blood_pressure  True
specific_gravity  True
albumin        True
sugar          True
red_blood_cells  True
pus_cell        True
pus_cell_clumps  True
bacteria        True
blood_glucose_random  True
blood_urea       True
serum_creatinine  True
sodium          True
potassium        True
hemoglobin       True
packed_cell_volume  True
white_blood_cell_count  True
red_blood_cell_count  True
hypertension      True
diabetesmellitus  True
coronary_artery_disease  True
appetite          True
pedal_edema       True
anemia            True
class            False
```

```

data.isnull().sum()

```

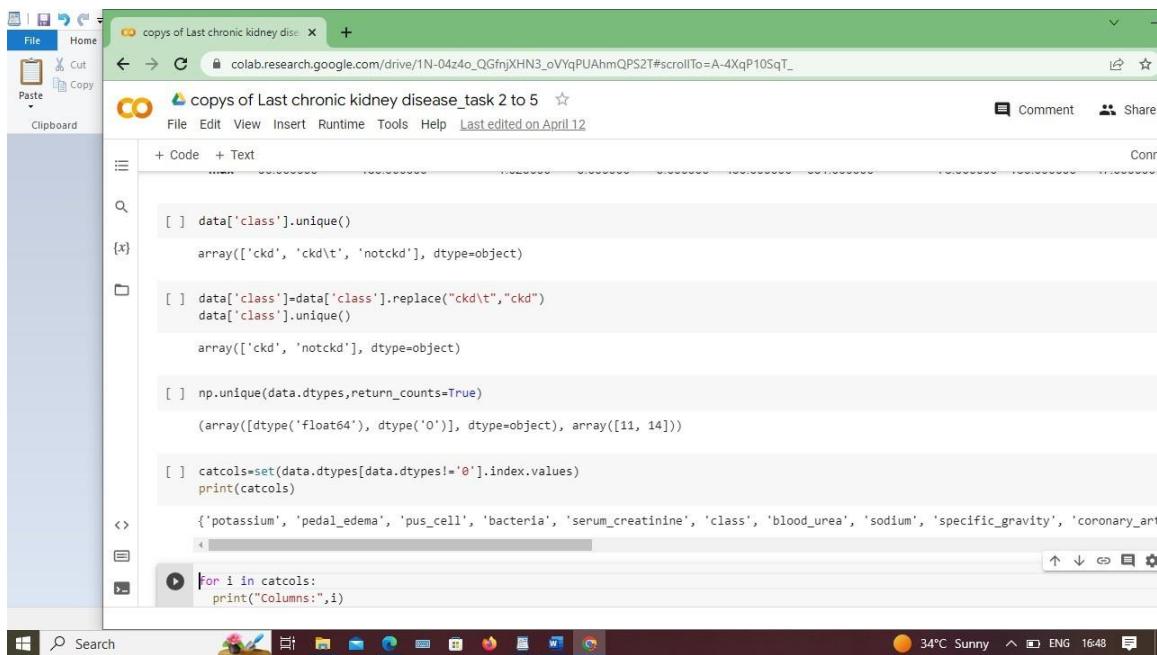
	age	9
{x}	blood_pressure	12
	specific_gravity	47
	albumin	46
	sugar	49
	red_blood_cells	152
	pus_cell	65
	pus_cell_clumps	4
	bacteria	4
	blood glucose random	44
	blood_urea	19
	serum_creatinine	17
	sodium	87
	potassium	88
	hemoglobin	52
	packed_cell_volume	70
	white_blood_cell_count	105
	red_blood_cell_count	130
	hypertension	2
	diabetesmellitus	2
	coronary_artery_disease	2
	appetite	1
	pedal_edema	1
	anemia	1
	class	0

```

data.describe()

```

	age	blood_pressure	specific_gravity	albumin	sugar	blood glucose random	blood_urea	serum_creatinine	sodium	potassium
<b>count</b>	391.000000	388.000000	353.000000	354.000000	351.000000	356.000000	381.000000	383.000000	313.000000	312.000000
<b>mean</b>	51.483376	76.469072	1.017408	1.016949	0.450142	148.036517	57.425722	3.072454	137.528754	4.627244
<b>std</b>	17.169714	13.683637	0.005717	1.352679	1.099191	79.281714	50.503006	5.741126	10.408752	3.193904
<b>min</b>	2.000000	50.000000	1.005000	0.000000	0.000000	22.000000	1.500000	0.400000	4.500000	2.500000
<b>25%</b>	42.000000	70.000000	1.010000	0.000000	0.000000	99.000000	27.000000	0.900000	135.000000	3.800000
<b>50%</b>	55.000000	80.000000	1.020000	0.000000	0.000000	121.000000	42.000000	1.300000	138.000000	4.400000
<b>75%</b>	64.500000	80.000000	1.020000	2.000000	0.000000	163.000000	66.000000	2.800000	142.000000	4.900000
<b>max</b>	90.000000	180.000000	1.025000	5.000000	5.000000	490.000000	391.000000	76.000000	163.000000	47.000000



```

[ ] data['class'].unique()
{x}
array(['ckd', 'ckd\|t', 'notckd'], dtype=object)

[ ] data['class']=data['class'].replace("ckd\|t","ckd")
data['class'].unique()

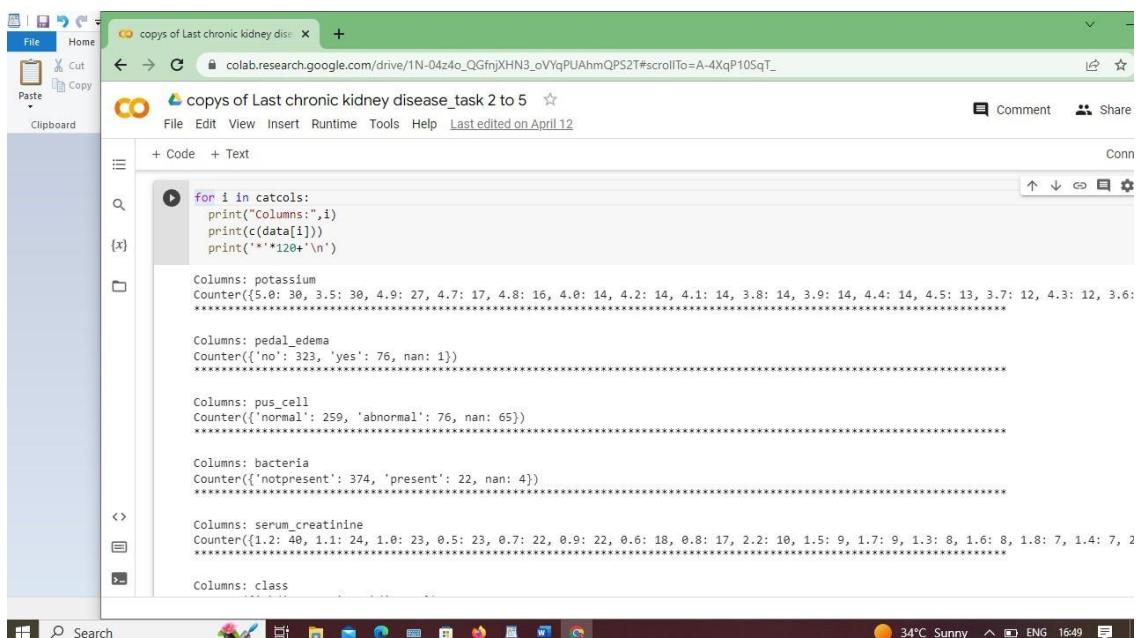
array(['ckd', 'notckd'], dtype=object)

[ ] np.unique(data.dtypes,return_counts=True)
(array([dtype('float64'), dtype('O')], dtype=object), array([11, 14]))

[ ] catcols=set(data.dtypes[data.dtypes!='O'].index.values)
print(catcols)

{'potassium', 'pedal_edema', 'pus_cell', 'bacteria', 'serum_creatinine', 'class', 'blood_urea', 'sodium', 'specific_gravity', 'coronary_ar
<>
[ ]
for i in catcols:
    print("Columns:",i)

```



```

for i in catcols:
    print("Columns:",i)
    print(c(data[i]))
    print('***'*120+'\n')

Columns: potassium
Counter({5.0: 30, 3.5: 30, 4.9: 27, 4.7: 17, 4.8: 16, 4.0: 14, 4.2: 14, 4.1: 14, 3.8: 14, 3.9: 14, 4.4: 14, 4.5: 13, 3.7: 12, 4.3: 12, 3.6:
*****'***'*120+'***'*120+'\n'

Columns: pedal_edema
Counter({'no': 323, 'yes': 76, nan: 1})
*****'***'*120+'***'*120+'\n'

Columns: pus_cell
Counter({'normal': 259, 'abnormal': 76, nan: 65})
*****'***'*120+'***'*120+'\n'

Columns: bacteria
Counter({'notpresent': 374, 'present': 22, nan: 4})
*****'***'*120+'***'*120+'\n'

Columns: serum_creatinine
Counter({1.2: 40, 1.1: 24, 1.0: 23, 0.5: 23, 0.7: 22, 0.9: 22, 0.6: 18, 0.8: 17, 2.2: 10, 1.5: 9, 1.7: 9, 1.3: 8, 1.6: 8, 1.8: 7, 1.4: 7, 2
*****'***'*120+'***'*120+'\n'

Columns: class

```



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Clipboard

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+ Code + Text

```
Continuous Columns: appetite
[x] contcols.remove('specific_gravity')
contcols.remove('albumin')
contcols.remove('sugar')
print(contcols)

['potassium', 'pedal_edema', 'pus_cell', 'bacteria', 'serum_creatinine', 'class', 'blood_urea', 'sodium', 'coronary_artery_disease', 'diabe
[ ] contcols.add('red_blood_cell_count')
contcols.add('packed_cell_volume')
contcols.add('white_blood_cell_count')
print(contcols)

{'potassium', 'pedal_edema', 'pus_cell', 'bacteria', 'serum_creatinine', 'class', 'blood_urea', 'sodium', 'coronary_artery_disease', 'diabe
[ ] catcols.add('specific_gravity')
catcols.add('albumin')
catcols.add('sugar')
print(catcols)
```

Conn

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```
[ ] data['coronary_artery_disease']=data.coronary_artery_disease.replace('\tno','no')
[ ] {data['coronary_artery_disease']}
```

(x) Counter({'no': 364, 'yes': 34, nan: 2})

```
[ ] data['diabetesmellitus']=data.diabetesmellitus.replace(to_replace={'\tno':'no','\tyes':'yes','yes':'yes'})
[ ] c(data['diabetesmellitus'])

Counter({'yes': 136, 'no': 261, 'yes': 1, nan: 2})
```

```
[ ] data.isnull().any()
```

Column	Value
age	True
blood_pressure	True
specific_gravity	True
albumin	True
sugar	True
red_blood_cells	True
pus_cell	True
pus_cell_clumps	True
bacteria	True
blood_glucose_random	True
blood_urea	True
serum_creatinine	True
sodium	True
Glucose	True

Conn

34°C Sunny ENG 16:52

File | Home

copy of Last chronic kidney disease

colab.research.google.com/drive/1N-04z4o\_QGfnjXHN3\_oVYqPUAhmQPS2T#scrollTo=8fnT33n8VK1W

Comment Share

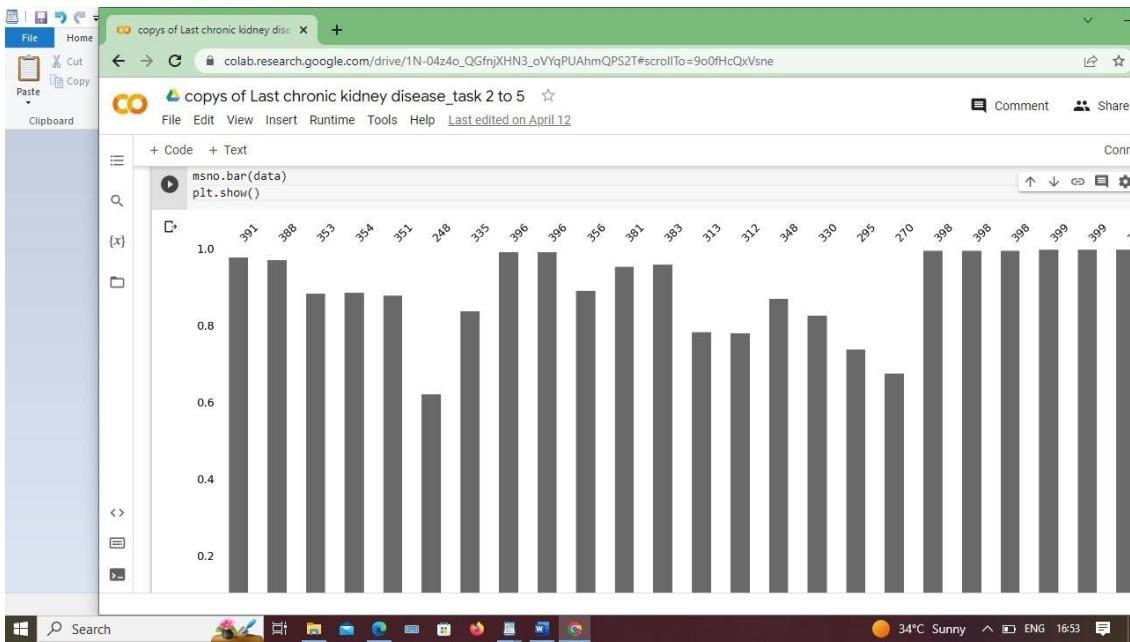
+ Code + Text

data.isnull().sum()

```
[{x}: age 9  
blood_pressure 12  
specific_gravity 47  
albunin 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  
hemoglobin 52  
packed_cell_volume 70  
white_blood_cell_count 105  
red_blood_cell_count 130  
hypertension 2  
diabetesmellitus 2  
coronary_artery_disease 2  
appetite 1  
pedal_edema 1  
anemia 1  
slacks 0]
```

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```

[ ] data.packed_cell_volume = pd.to_numeric(data.packed_cell_volume, errors='coerce')
data.white_blood_cell_count = pd.to_numeric(data.white_blood_cell_count, errors='coerce')
data.red_blood_cell_count = pd.to_numeric(data.red_blood_cell_count, errors='coerce')

data['blood glucose random'].fillna(data['blood glucose random'].mean(), inplace=True)
data['blood_pressure'].fillna(data['blood_pressure'].mean(), inplace=True)
data['blood_urea'].fillna(data['blood_urea'].mean(), inplace=True)
data['hemoglobin'].fillna(data['hemoglobin'].mean(), inplace=True)
data['packed_cell_volume'].fillna(data['packed_cell_volume'].mean(), inplace=True)
data['potassium'].fillna(data['potassium'].mean(), inplace=True)
data['red_blood_cell_count'].fillna(data['red_blood_cell_count'].mean(), inplace=True)
data['serum_creatinine'].fillna(data['serum_creatinine'].mean(), inplace=True)
data['sodium'].fillna(data['sodium'].mean(), inplace=True)
data['white_blood_cell_count'].fillna(data['white_blood_cell_count'].mean(), inplace=True)

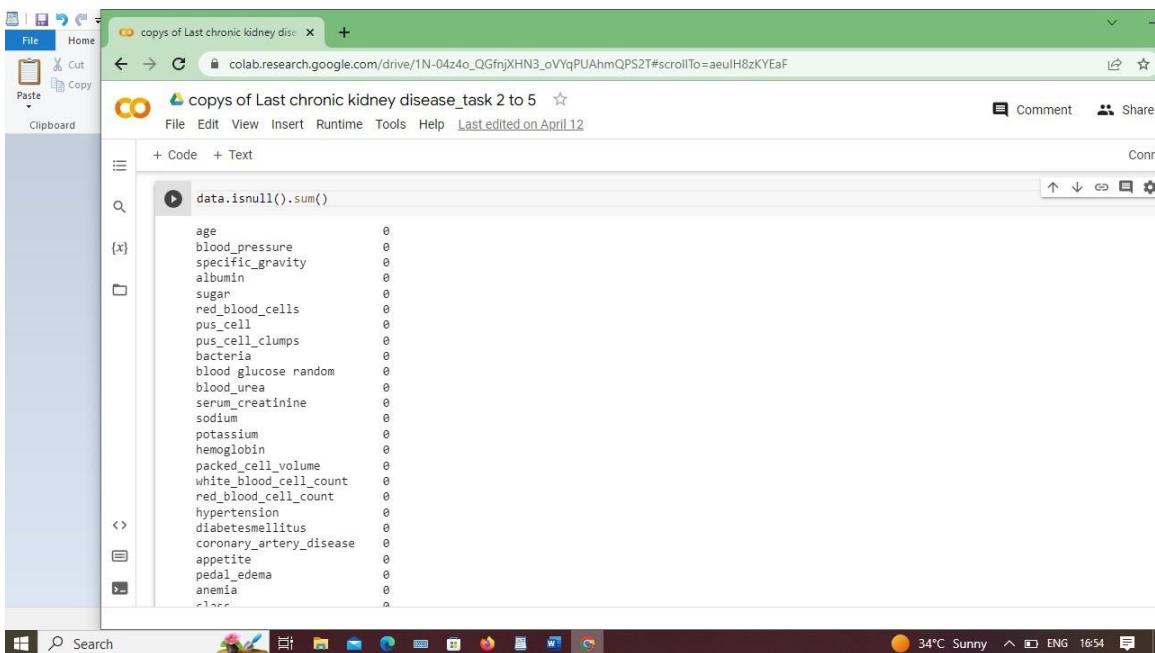
```

```

[ ] data['age'].fillna(data['age'].mode()[0], inplace=True)
data['hypertension'].fillna(data['hypertension'].mode()[0], inplace=True)
data['pus_cell_clumps'].fillna(data['pus_cell_clumps'].mode()[0], inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0], inplace=True)
data['albumin'].fillna(data['albumin'].mode()[0], inplace=True)
data['pus_cell'].fillna(data['pus_cell'].mode()[0], inplace=True)
data['red_blood_cells'].fillna(data['red_blood_cells'].mode()[0], inplace=True)
data['coronary_artery_disease'].fillna(data['coronary_artery_disease'].mode()[0], inplace=True)
data['bacteria'].fillna(data['bacteria'].mode()[0], inplace=True)
data['anemia'].fillna(data['anemia'].mode()[0], inplace=True)
data['sugar'].fillna(data['sugar'].mode()[0], inplace=True)
data['diabetesmellitus'].fillna(data['diabetesmellitus'].mode()[0], inplace=True)
data['pedal_edema'].fillna(data['pedal_edema'].mode()[0], inplace=True)
data['specific_gravity'].fillna(data['specific_gravity'].mode()[0], inplace=True)

[ ] data.isnull().sum()

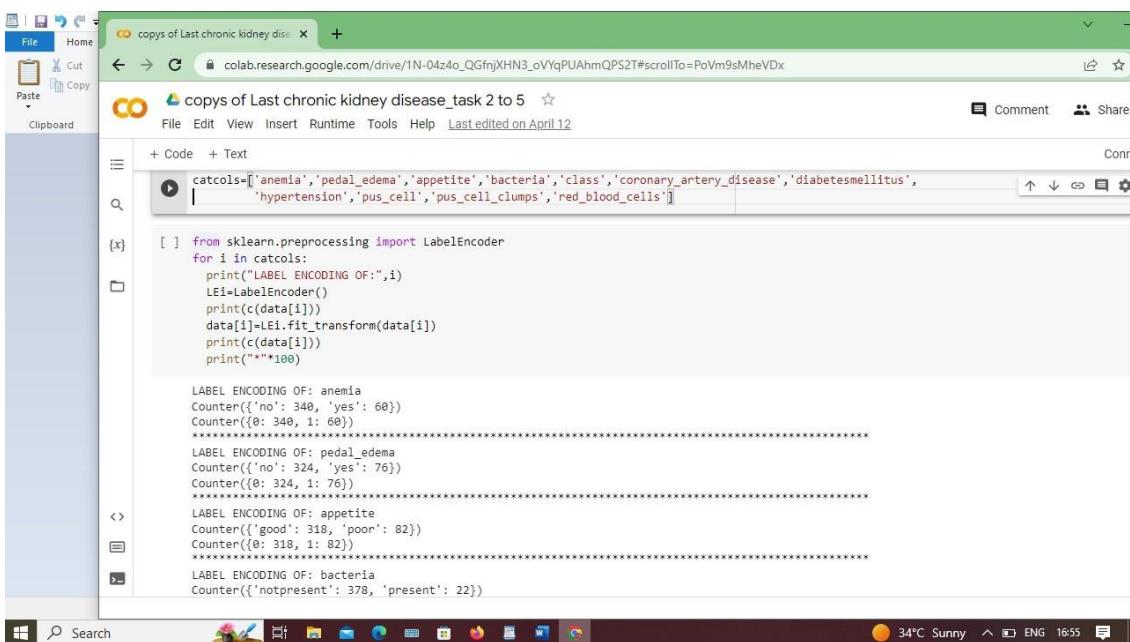
```



copies of Last chronic kidney disease\_task 2 to 5

```
data.isnull().sum()

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
hemoglobin   0
packed_cell_volume 0
white_blood_cell_count 0
red_blood_cell_count 0
hypertension   0
diabetesmellitus 0
coronary_artery_disease 0
appetite      0
pedal_edema   0
anemia        0
class         0
```

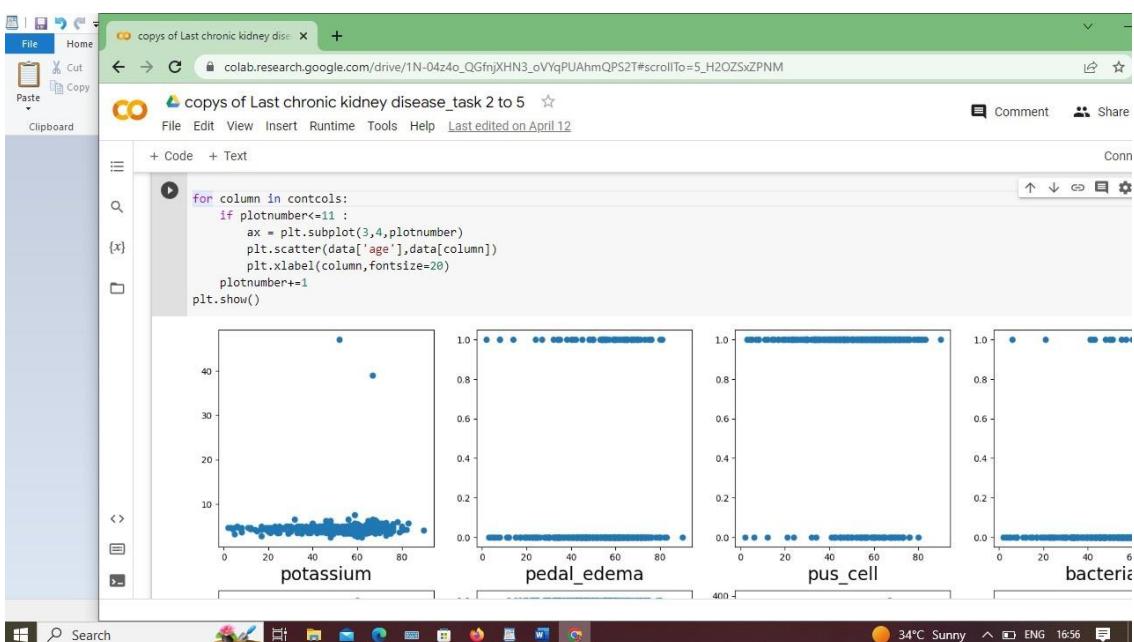
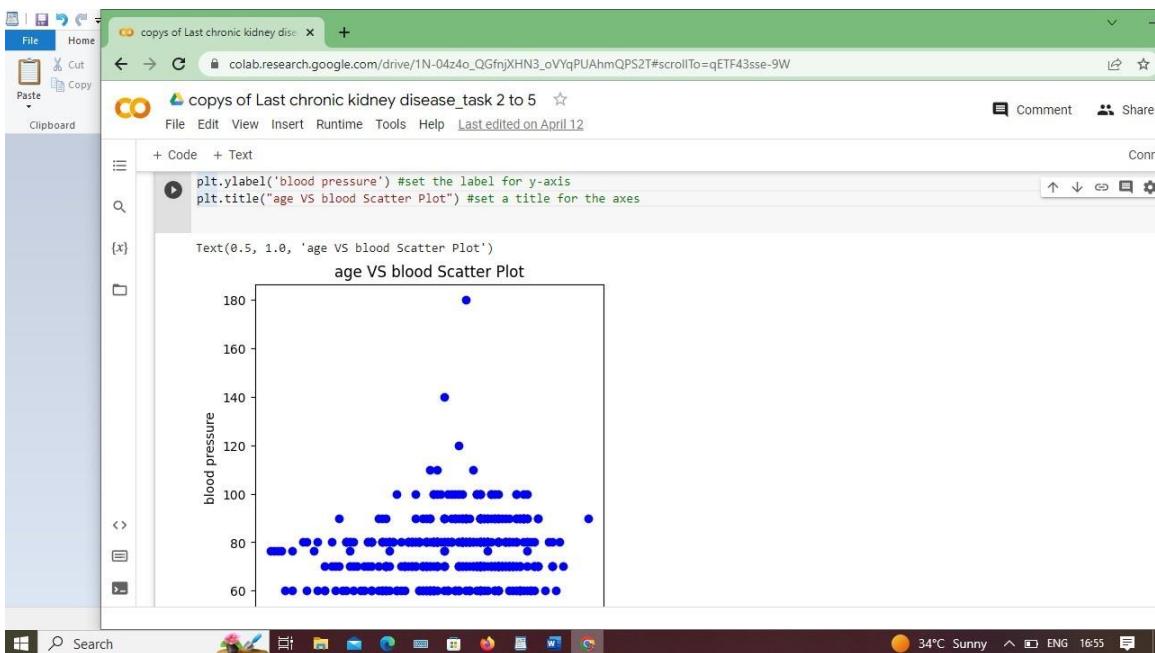


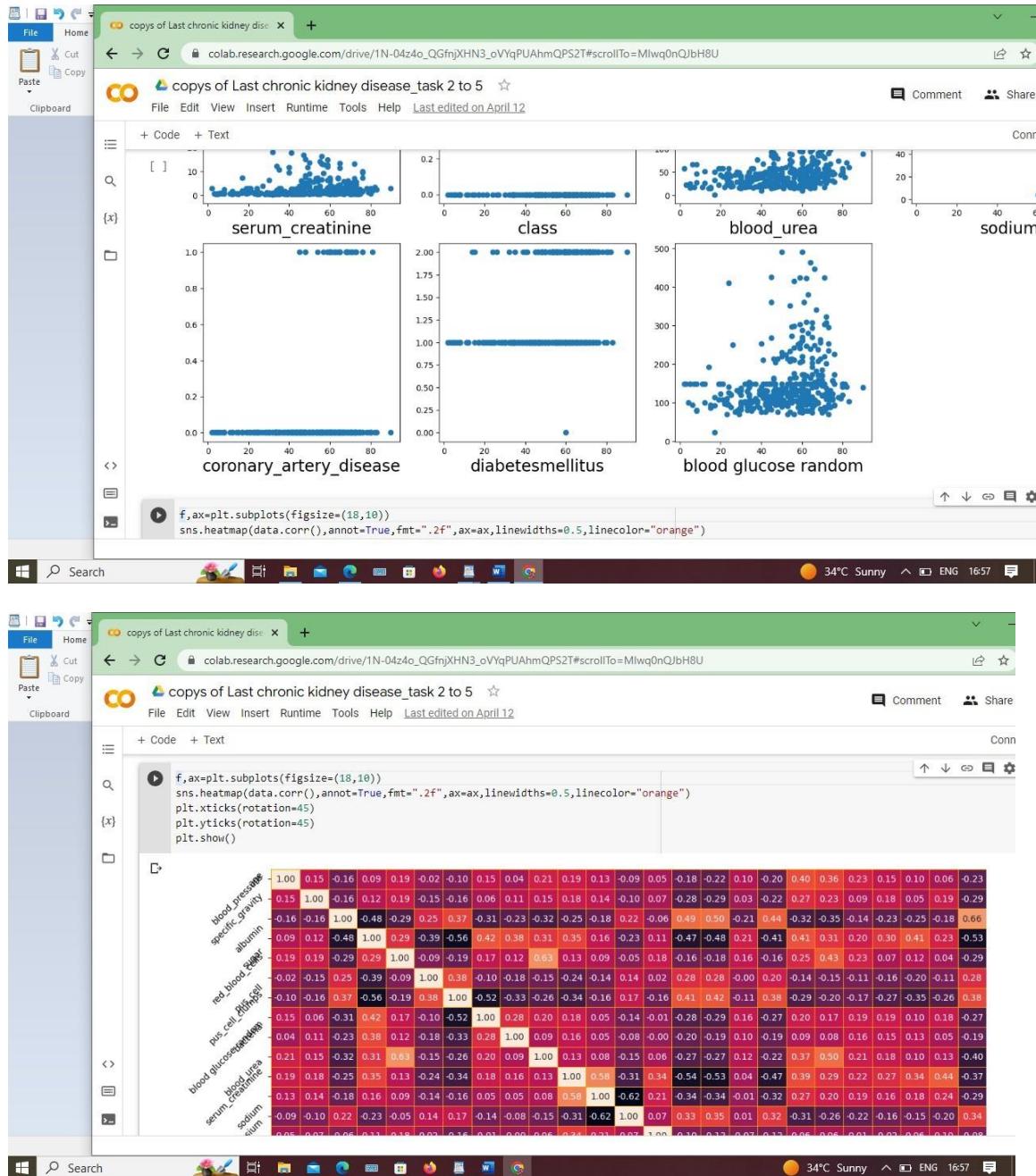
copies of Last chronic kidney disease\_task 2 to 5

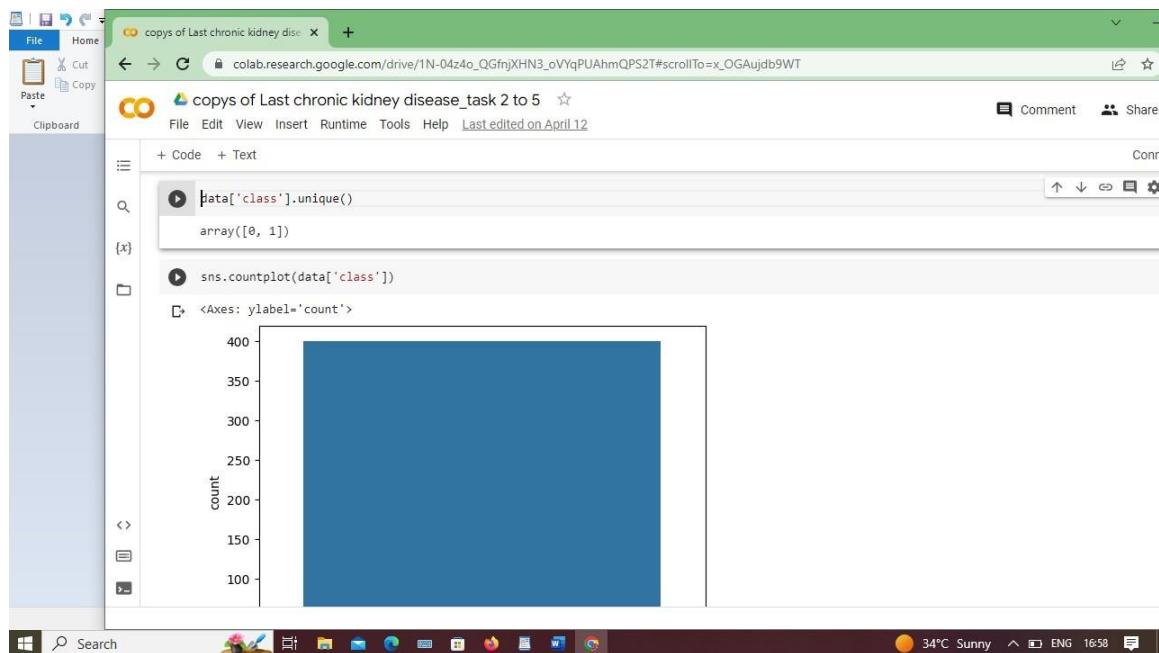
```
catcols=['anemia','pedal_edema','appetite','bacteria','class','coronary_artery_disease','diabetesmellitus','hypertension','pus_cell','pus_cell_clumps','red_blood_cells']

[ ] from sklearn.preprocessing import LabelEncoder
for i in catcols:
    print("LABEL ENCODING OF:",i)
    LEi=LabelEncoder()
    print(c(data[1]))
    data[1]=LEi.fit_transform(data[1])
    print(c(data[1]))
    print("*****100")

    LABEL ENCODING OF: anemia
    Counter({'no': 340, 'yes': 60})
    Counter({0: 340, 1: 60})
    *****
    LABEL ENCODING OF: pedal_edema
    Counter({'no': 324, 'yes': 76})
    Counter({0: 324, 1: 76})
    *****
    LABEL ENCODING OF: appetite
    Counter({'good': 318, 'poor': 82})
    Counter({0: 318, 1: 82})
    *****
    LABEL ENCODING OF: bacteria
    Counter({'notpresent': 378, 'present': 22})
```







```

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[ ] selcols=['red_blood_cells','pus_cell','blood_glucose_random','blood_urea','pedal_edema','anemia','diabetesmellitus','coronary_artery_disease']
x=pd.DataFrame(data,columns=selcols)
y=pd.DataFrame(data,columns=['class'])
print(x.shape)
print(y.shape)

(400, 8)
(400, 1)

[ ] from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=2)#train test split
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)

(320, 8)
(320, 1)
(80, 8)
(80, 1)

[ ] from sklearn.linear_model import LogisticRegression
lgr = LogisticRegression()
lgr.fit(x_train,y_train)

```

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```
y_pred = lgr.predict([[129,99,1,0,0,1,0,1]])  
print(y_pred)  
(y_pred)  
[1]  
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticRegression was fit  
warnings.warn(  
array([1])  
  
[ ] y_pred = lgr.predict(x_test)  
  
[ ] accuracy_score(y_test,y_pred)  
0.9125  
  
[ ] conf_mat = confusion_matrix(y_test,y_pred)  
conf_mat  
array([[47,  7],  
       [ 0, 26]])
```

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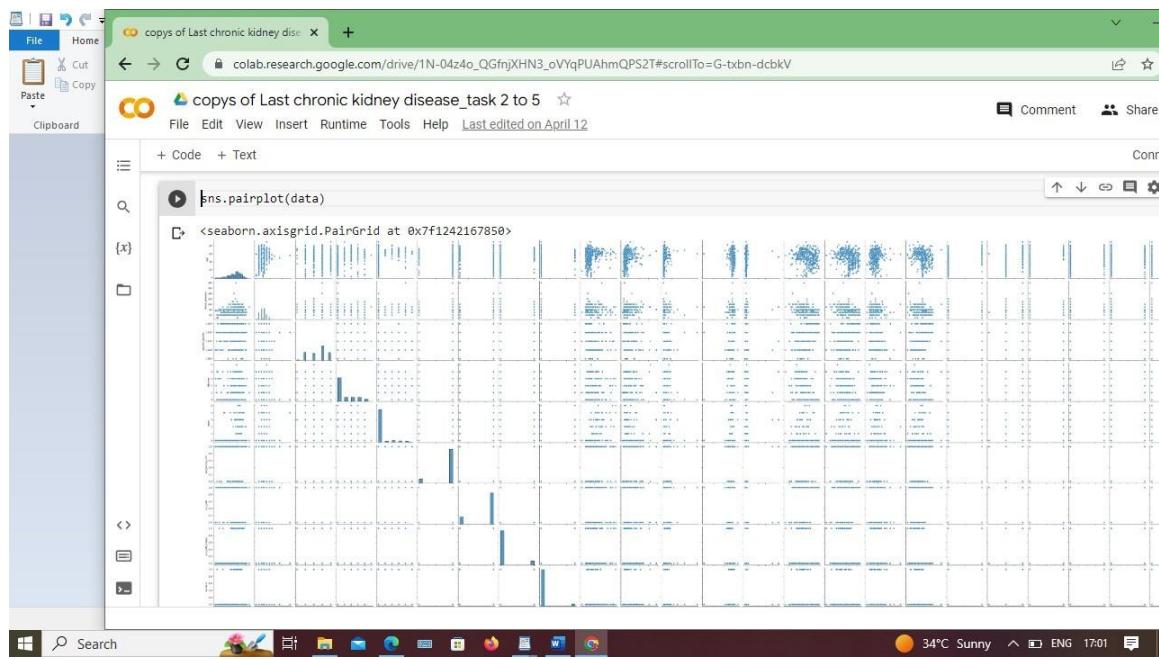
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```
pickle.dump(lgr, open('CKD.pk1','wb'))
```

contcols

{'age',  
'anemia',  
'appetite',  
'bacteria',  
'blood glucose\_random',  
'blood\_pressure',  
'blood\_urea',  
'class',  
'coronary\_artery\_disease',  
'diabetesmellitus',  
'hemoglobin',  
'hypertension',  
'packed\_cell\_volume',  
'pedal\_edema',  
'potassium',  
'pus\_cell',  
'pus\_cell\_clumps',  
'red\_blood\_cell\_count',  
'red\_blood\_cells',  
'serum\_creatinine',  
'sodium',  
'white\_blood\_cell\_count'}

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A screenshot of a Google Colab notebook titled "copies of Last chronic kidney disease\_task 2 to 5". The notebook interface includes a toolbar with File, Home, Paste, Cut, Copy, and Clipboard options. The main area shows a code cell with the command `sc=StandardScaler()` and `x_bal=sc.fit_transform(x)`. Below the code, a variable `y` is defined, which contains a list of values labeled "class".

	class
0	0
1	0
2	0
3	0
4	0
...	...
395	1
396	1
397	1
398	1
399	1

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```

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=2)

[ ] x.head()

      red_blood_cells  pus_cell  blood glucose random  blood_urea  pedal_edema  anemia  diabetesmellitus  coronary_artery_disease
0           1          1    121.000000   36.0       0       0        2          0
1           1          1    148.036517   18.0       0       0        1          0
2           1          1    423.000000   53.0       0       1        2          0
3           1          0    117.000000   56.0       1       1        1          0
4           1          1    106.000000   26.0       0       0        1          0

```

```

[ ] pd.DataFrame(x_bal)

      0      1      2      3      4      5      6      7
0  0.36489  0.484322 -0.361987 -0.435268 -0.484322 -0.420084  1.385651 -0.304789
1  0.36489  0.484322  0.000000 -0.800941 -0.484322 -0.420084 -0.705897 -0.304789
2  0.36489  0.484322  3.681441 -0.089909 -0.484322  2.380476  1.385651 -0.304789

```

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```

from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_bal=sc.fit_transform(x)

[ ] import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

[ ] classification = Sequential()
classification.add(Dense(30,activation='relu'))
classification.add(Dense(128,activation='relu'))
classification.add(Dense(64,activation='relu'))
classification.add(Dense(32,activation='relu'))
classification.add(Dense(1,activation='sigmoid'))

[ ] classification.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])

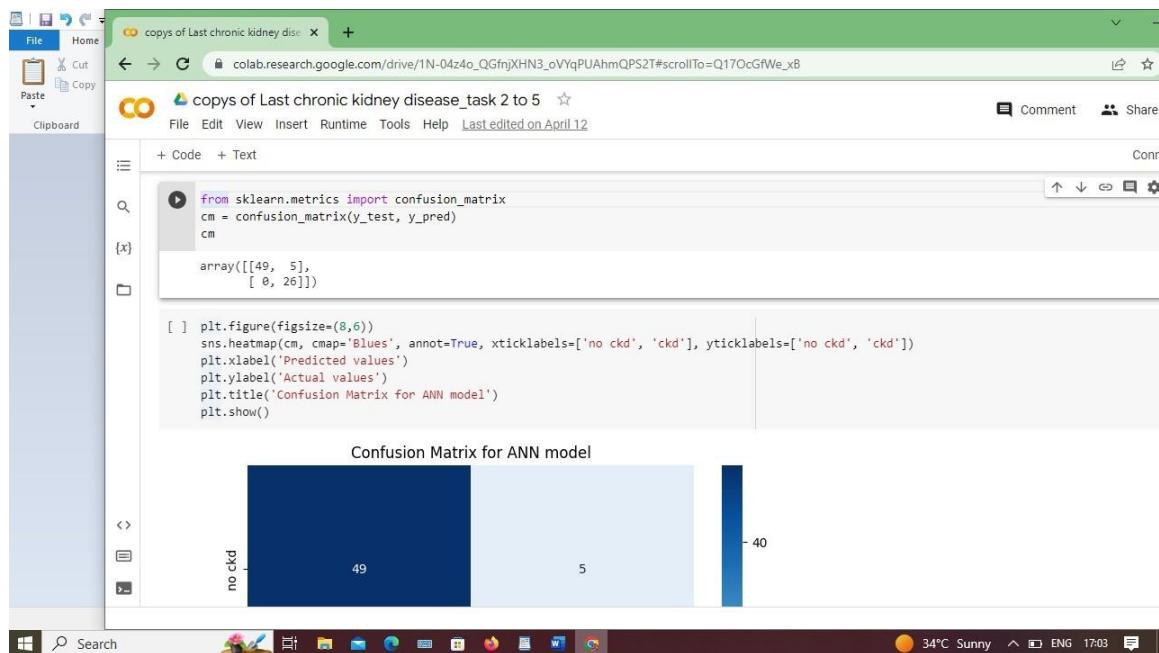
[ ] classification.fit(x_train,y_train,batch_size=10,validation_split=0.2,epochs=100)

```

```

Epoch 1/100
26/26 [=====] - 3s 14ms/step - loss: 0.7780 - accuracy: 0.5938 - val_loss: 0.5363 - val_accuracy: 0.6875
Epoch 2/100

```



The screenshot shows a Google Colab notebook titled "copies of Last chronic kidney disease\_task 2 to 5". The code cell contains the following Python code:

```

from sklearn.metrics import accuracy_score,classification_report
score = accuracy_score(y_pred,y_test)
print('The accuracy for ANN model is: {}%'.format(score*100))

The accuracy for ANN model is: 93.75%

```

```

def predict_exit(sample_value):
    # Convert list to numpy array
    sample_value = np.array(sample_value)

    # Reshape because sample_value contains only 1 record
    sample_value = sample_value.reshape(1, -1)

    # Feature Scaling
    sample_value = sc.transform(sample_value)

    return classifier.predict(sample_value)

```

```

x.head()

```

```

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+ Code + Text
[ ] x.head()
{x}
red_blood_cells  pus_cell  blood glucose random  blood_urea  pedal_edema  anemia  diabetesmellitus  coronary_artery_disease
0 1 1 121.000000 36.0 0 0 2 0
1 1 1 148.036517 18.0 0 0 1 0
2 1 1 423.000000 53.0 0 1 2 0
3 1 0 117.000000 56.0 1 1 1 0
4 1 1 106.000000 26.0 0 0 1 0

[ ] test=classification.predict([[1,1,121.000000,36.0,0,0,1,0]])
if test==1:
    print('Prediction: High chance of CKD!')
else:
    print('Prediction: Low chance of CKD.')
1/1 [=====] - 0s 140ms/step
Prediction: Low chance of CKD.

[ ] print(classification_report(y_test, y_pred))

```

```

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+ Code + Text
[ ] from sklearn.linear_model import LogisticRegression
lgr = LogisticRegression()
lgr.fit(x_train,y_train)
/usr/local/lib/python3.9/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array
y = column_or_1d(y, warn=True)
* LogisticRegression
LogisticRegression()

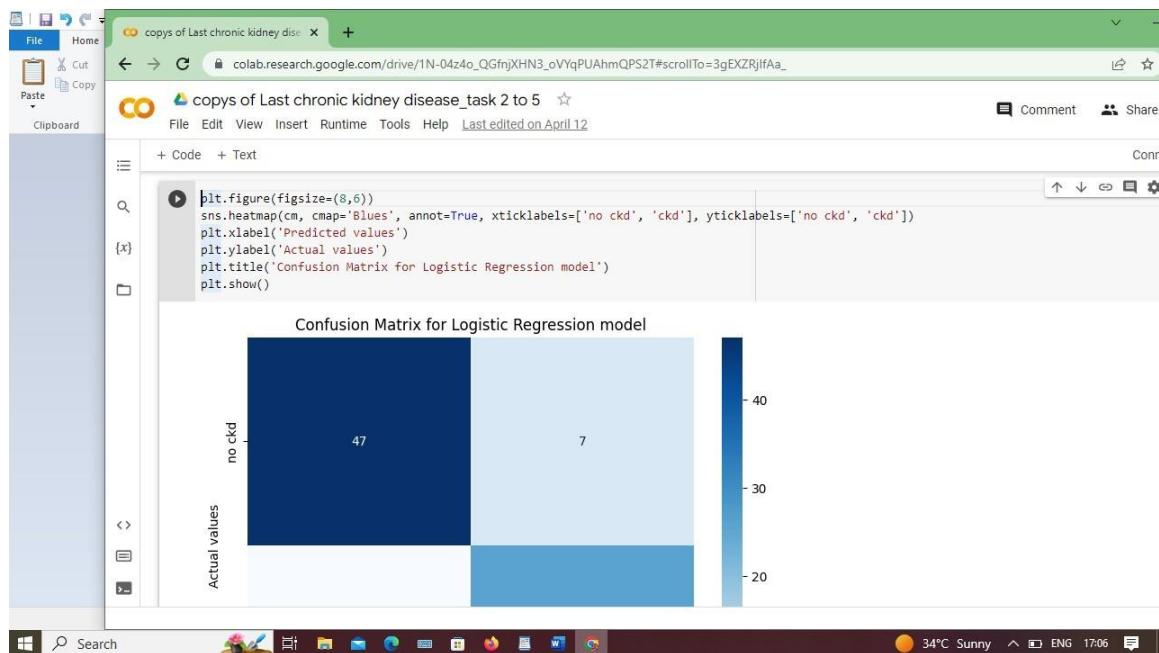
[ ] from sklearn.metrics import accuracy_score,classification_report
y_predict = lgr.predict(x_test)

[ ] print('Train accuracy score of LOG_RE:',lgr.score(x_train, y_train))
print('Test accuracy score of LOG_RE:',lgr.score(x_test, y_test))

Train accuracy score of LOG_RE: 0.909375
Test accuracy score of LOG_RE: 0.9125

[ ] from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predict)

```



```
[ ] plt.figure(figsize=(8,6))
sns.heatmap(cm, cmap='Blues', annot=True, xticklabels=['no ckd', 'ckd'], yticklabels=['no ckd', 'ckd'])
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.title('Confusion Matrix for Logistic Regression model')
plt.show()

[ ] def logistic(x_train,x_test,y_train,y_test):
    lgr.fit(x_train,y_train)
    y_predict = lgr.predict(x_test)
    print("")

[ ] def Logistic(x_train,x_test,y_train,y_test):
    lgr=LogisticRegression()
    logistic=lgr.fit(x_train,y_train)
    predict_logistic=logistic.predict(x_test)
    training_accuracy=logistic.score(x_train,y_train)
    testing_accuracy=logistic.score(x_test,y_test)
    print("**** Logistic Regression ****")
    print("Training Accuracy : ",training_accuracy)
    print("Testing Accuracy : ",testing_accuracy)
    print("Accuracy Score : ",accuracy_score(y_test,predict_logistic))
    print("** Confusion Matrix **")
    print(confusion_matrix(y_test,predict_logistic))
    print("** Classification Report **")
    print(classification_report(y_test,predict_logistic))

[ ] Logistic(x_train,x_test,y_train,y_test)
```

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```
[ ] Logistic(x_train,x_test,y_train,y_test)

*** Logistic Regression ***
Training Accuracy : 0.909375
Testing Accuracy : 0.9125
Accuracy Score : 0.9125
** Confusion Matrix **
[[47  7]
 [ 0 26]]
** Classification Report **
precision    recall   f1-score   support
          0       1.00      0.87      0.93      54
          1       0.79      1.00      0.88      26

accuracy                           0.91
macro avg                           0.89
weighted avg                        0.91

/usr/local/lib/python3.9/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array
y = column_or_1d(y, warn=True)
```

print (classification\_report(y\_test, y\_predict))

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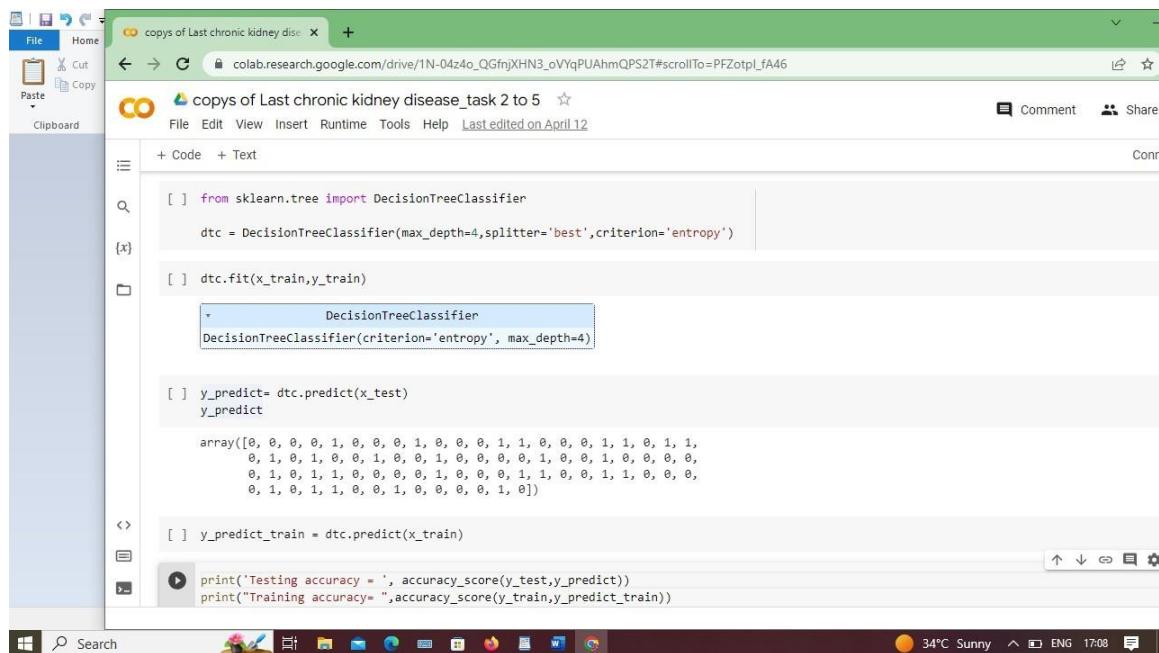
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```
[ ] y_pred = lgr.predict([[129,99,1,0,0,1,0,1]])
print(y_pred)
(y_pred)
[1]
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticRegression was fit
warnings.warn(
array([1])

[ ] y_pred = lgr.predict([[1,1,121.000000,36.0,0,0,1,0]])
print(y_pred)
(y_pred)
[1]
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticRegression was fit
warnings.warn(
array([1])

[ ] from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(max_depth=4,splitter='best',criterion='entropy')
```

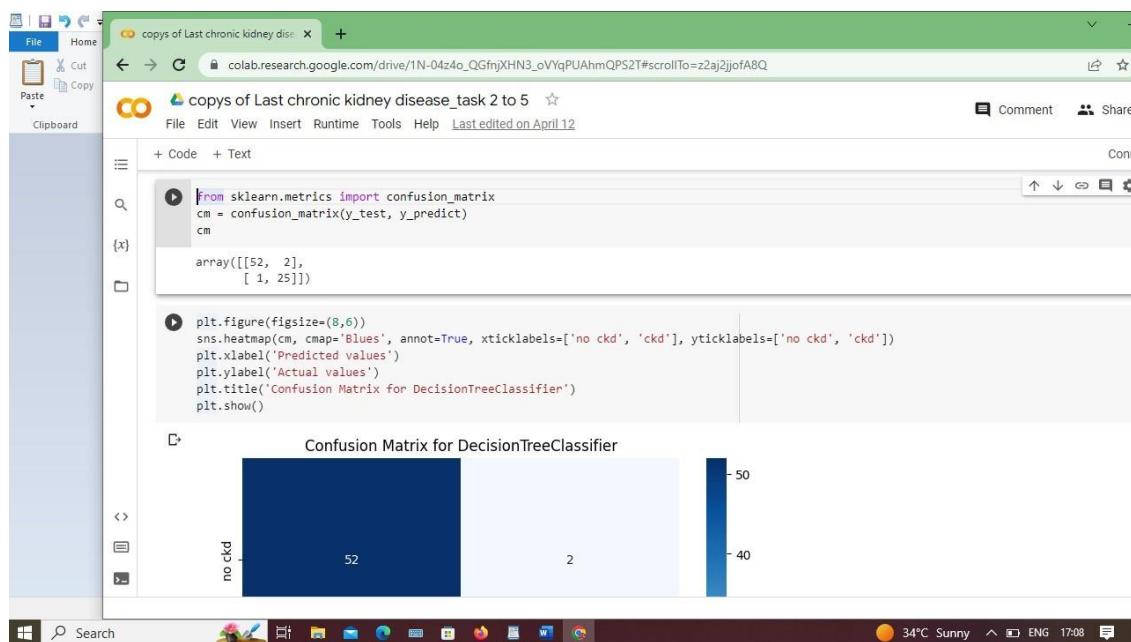
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```

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from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(max_depth=4, splitter='best', criterion='entropy')
dtc.fit(x_train, y_train)
y_predict = dtc.predict(x_test)
y_predict
array([0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0])
y_predict_train = dtc.predict(x_train)
print("Testing accuracy = ", accuracy_score(y_test, y_predict))
print("Training accuracy = ", accuracy_score(y_train, y_predict_train))

```



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```
[ ] precision recall f1-score support
[ ]          0     0.98    0.96    0.97    54
[ ]          1     0.93    0.96    0.94    26
[ ] accuracy      0.96    0.96    0.96    80
[ ] macro avg     0.95    0.96    0.96    80
[ ] weighted avg  0.96    0.96    0.96    80

[ ] from sklearn.ensemble import RandomForestClassifier
[ ] rfc = RandomForestClassifier(n_estimators=10,criterion='entropy')

[ ] rfc.fit(x_train,y_train)
<ipython-input-104-b87bb2ba9825>:1: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the sha
[ ] rfc.fit(x_train,y_train)
[ ] RandomForestClassifier
[ ] RandomForestClassifier(criterion='entropy', n_estimators=10)

[ ] y_predict = rfc.predict(x_test)
```

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```
[ ] y_predict = rfc.predict(x_test)

[ ] y_predict_train = rfc.predict(x_train)

[ ] print('Training accuracy: ',accuracy_score(y_train,y_predict_train))
[ ] print('Testing accuracy: ',accuracy_score(y_test,y_predict))

[ ] Training accuracy:  0.9875
[ ] Testing accuracy:  0.9375

[ ] from sklearn.metrics import confusion_matrix
[ ] cm = confusion_matrix(y_test, y_predict)
[ ] cm

[ ] array([[52,  2],
       [ 3, 23]])

[ ] print(classification_report(y_test,y_predict))

[ ] precision recall f1-score support
[ ]          0     0.95    0.96    0.95    54
[ ]          1     0.93    0.96    0.94    26
```

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```

y_train.value_counts()

class
0    196
1    124
dtype: int64

models = [
    ('LogReg', LogisticRegression()),
    ('RF', RandomForestClassifier()),
    ('DecisionTree', DecisionTreeClassifier()),
    ('ANN', MLPClassifier())
]

```

```

from flask import flask, render_template, request
import numpy as np
import pickle
app = Flask(__name__)
model = pickle.load(open('CKD.pkl', 'rb'))
@app.route('/')
def home():
    return render_template('home.html')
@app.route('/prediction', methods=['post', 'GET'])
def prediction():
    return render_template('indexnew.html')
@app.route('/predict', methods=[POST])
def predict():
    input_features = [float(x) for x in request.form.values()]
    features_values = [np.array(input_features)]
    features_name = ['blood_ureal', 'blood glucose random', 'anemia', 'coronary_artery_disease', 'pus_cell', 'red_bloodcells', 'diabetesmellitus', 'pedal']
    df = pd.DataFrame(features_values, columns=features_name)
    output = model.predict(df)
    return render_template('result.html', prediction_text=output)
if __name__ == '__main__':
    app.run(debug=True)

```



