```
import pandas as pd
import numpy as np
a=pd.read_csv("/content/drive/MyDrive/minor-/food_data_1_missing_values_real.csv")
b=pd.read_csv("/content/drive/MyDrive/minor-/FOOD-DATA-GROUP2.csv")
c=pd.read_csv("/content/drive/MyDrive/minor-/FOOD-DATA-GROUP3.csv")
d=pd.read_csv("/content/drive/MyDrive/minor-/food_data_4_missing_real.csv")
e=pd.read_csv("/content/drive/MyDrive/minor-/FOOD-DATA-GROUP5.csv")

#Merge 5 dataset
data = pd.concat([a,b,c,d,e], axis=0)
print(data)
```

\rightarrow		Unnamed:	0.1	Unnamed	: 0					food	\		
	0		0		0				cre	am cheese			
	1		1		1			neu	fchat	el cheese			
	2		2		2	requeijao	crem	050	light	catupiry			
	3		3		3	. 3			ricot	ta cheese			
	4		4		4		cr	eam	chees	e low fat			
	717		717	7	717					jews ear			
	718		718	7	718	enoki mushrooms							
	719		719	7	719	morel mushrooms							
	720		720	7	720	portabella mushrooms raw							
	721		721	7	721	oyster mushroom							
		Caloric \	/alue	Fat	Sat	turated Fa	ts M	lonou	nsatıı	rated Fat	s \		
	0	carol ic	51.0	5.000	Ju	2.9		onou		1.30	- •		
	1		215.0	19.400		10.9				4.90			
	2	•	49.0	NaN		2.3				0.90			
	3		30.0	2.000		1.3				0.50			
	4		30.0	2.300		1.4				0.60			
	717		25.0	0.095		0.0				0.00			
	718		1.0	0.099		0.0	27			0.00	0		
	719		4.0	0.070		0.0	56			0.03			
	720		19.0	0.300		0.0	36			0.01	.6		
	721		5.0	0.035		0.0				0.03	9		
							_				_	_	
	_	Polyunsa	turate		Cart	oohydrates	_		• • •	Calcium	Copper	Iron	\
	0			0.200		0.8		500	• • •	0.008	14.100	0.082	
	1			0.800		3.1		700	• • •	99.500	0.034	0.100	
	2			0.000		0.9		400	• • •	0.000	0.000	0.000	
	3			0.002		1.5		091	• • •	0.097	41.200	0.097	
	4			0.042		1.2		900	• • •	22.200	0.072	0.008	
	 717			0.000		6.7		000	• • •	15.800	0.400	0.600	
	718			0.010		0.7		034		0.000	0.000	0.099	
	719					0.7		096					
	719 720			0.007 0.100		3.3		200	• • •	0.000 2.600	5.500 0.200	0.056 0.300	
	720			0.099		0.9		200	• • •	0.000	0.500	0.008	
	/ 21			0.055		0.9	υ.	200	• • •	0.000	0.500	0.000	

→

```
Magnesium Manganese Phosphorus Potassium Selenium Zinc \
     0
              0.027
                        1.300
                                    0.091
                                                15.5
                                                        19.100
                                                               0.039
     1
              8.500
                        0.088
                                  117.300
                                               129.2
                                                         0.054
                                                               0.700
     2
              0.000
                        0.000
                                    0.000
                                                 0.0
                                                         0.000
                                                               0.000
     3
              0.096
                        4.000
                                    0.024
                                                30.8
                                                        43.800
                                                               0.035
                                   22.800
     4
             1.200
                        0.098
                                                37.1
                                                         0.034
                                                               0.053
                ...
                          . . .
                                      . . .
                                                                  . . .
     717
             24.800
                        0.040
                                   13.900
                                                42.6
                                                         0.034 0.700
     718
             0.034
                        0.500
                                    0.015
                                                 3.2
                                                        10.800
                                                                0.096
     719
             1.600
                        2.500
                                    0.060
                                                25.0
                                                        53.000
                                                               0.069
     720
              0.000
                        0.092
                                   92.900
                                               313.0
                                                         0.015 0.500
     721
              0.200
                        2.700
                                    0.055
                                                18.0
                                                        63.000 0.048
          Nutrition Density
     0
                     7.070
                   130.100
    1
     2
                     5.400
     3
                     5.196
     4
                    27.007
from google.colab import drive
drive.mount('/content/drive')
→ Mounted at /content/drive
 #Step 1: Remove redundant columns
cleaned_data = data.drop(columns=['Unnamed: 0.1', 'Unnamed: 0'])
print(cleaned_data)
                                     food Caloric Value
                                                             Fat Saturated Fats \
```

0 1 2 3 4	neufc requeijao cremoso li ri	cream cheese hatel cheese ght catupiry cotta cheese eese low fat	51.0 215.0 49.0 30.0 30.0	5.000 19.400 NaN 2.000 2.300	1	2.900 0.900 2.300 1.300 1.400	
717		jews ear	25.0	0.095		0.000	
718	eno	ki mushrooms	1.0	0.099	99 0.027		
719	mor	el mushrooms	4.0	0.070		0.056	
720	portabella m	ushrooms raw	19.0	0.300		0.036	
721	oys	ter mushroom	5.0	0.035		0.016	
0 1 2 3 4	Monounsaturated Fats 1.300 4.900 0.900 0.500		0.200 0.800 0.000 0.002 0.042	0.8 3.1 0.9 1.5 1.2	0.500 2.700 3.400 0.091 0.900	\	
717	0.000		0.000	6.7	0.000		
718	0.000		0.010	0.2	0.034		
719	0.031		0.007	0.7	0.096		
720	0.016		0.100	3.3	2.200		
721	0.039		0.099	0.9	0.200		
0	Protein Dietary Fib			ron Magne 082 0	sium \ .027		

```
1
      7.800
                     0.000 ... 99.500
                                           0.034 0.100
                                                             8.500
2
       0.800
                     0.100 ...
                                   0.000
                                           0.000
                                                 0.000
                                                             0.000
3
      1.500
                     0.000 ...
                                   0.097
                                          41.200 0.097
                                                             0.096
4
      1.200
                     0.000 ...
                                  22.200
                                           0.072 0.008
                                                            1.200
                                     . . .
                       . . .
717
       0.500
                     0.000
                                  15.800
                                                  0.600
                                           0.400
                                                            24.800
718
      0.062
                     0.089
                                   0.000
                                           0.000
                                                  0.099
                                                             0.034
719
       0.400
                     0.400
                           . . .
                                   0.000
                                           5.500
                                                  0.056
                                                             1.600
720
      1.800
                     1.100 ...
                                   2.600
                                           0.200
                                                 0.300
                                                             0.000
721
      0.500
                     0.300
                                   0.000
                                           0.500 0.008
                                                             0.200
     Manganese
               Phosphorus Potassium Selenium
0
        1.300
                    0.091
                                15.5
                                        19.100
                                                0.039
```

Zinc Nutrition Density 7.070 1 0.088 117.300 129.2 0.054 0.700 130.100 2 0.000 0.000 0.0 0.000 0.000 5.400 3 4.000 0.024 30.8 43.800 0.035 5.196 4 0.098 22.800 37.1 0.034 0.053 27.007 . . . 717 0.040 13.900 42.6 0.034 0.700 24.249 718 0.015 3.2 10.800 0.096 0.433 0.500 1.727 719 2.500 0.060 25.0 53.000 0.069 720 0.092 92,900 313.0 0.015 0.500 9.400 721 1.804 2.700 0.055 18.0 63.000 0.048

[2395 rows x 35 columns]

Step 2: Drop duplicates
cleaned_data = cleaned_data.drop_duplicates()
print("\nData after removing duplicates:\n", cleaned_data)

0.031

0.016

 \overline{z}

719

720

Data after removing duplicates:

	. a. cc co.z aapzzc							
		food	Caloric	Value	Fat	Saturate	d Fats	
0	C	ream cheese		51.0	5.000		2.900	
1	neufch	atel cheese	2	215.0	19.400	1	0.900	
2	requeijao cremoso lig	ht catupiry		49.0	NaN		2.300	
3	ric	otta cheese		30.0	2.000		1.300	
4	cream che	ese low fat		30.0	2.300		1.400	
717		jews ear		25.0	0.095		0.000	
718	enok	i mushrooms		1.0	0.099		0.027	
719	more	l mushrooms		4.0	0.070		0.056	
720	portabella mu	shrooms raw		19.0	0.300		0.036	
721	oyst	er mushroom		5.0	0.035		0.016	
	Monounsaturated Fats	Polyunsatura	ted Fats	Carbo	ohydrates	Sugars	\	
0	1.300		0.200		0.8	-		
1	4.900		0.800		3.1	2.700		
2	0.900		0.000		0.9	3.400		
3	0.500		0.002		1.5	0.091		
4	0.600		0.042		1.2			
717	0.000		0.000		6.7			
718	0.000		0.010		0.2	0.034		

0.007

0.100

0.7

3.3

0.096

2.200

721 0.039 0.099 0.9 0.200 Protein Dietary Fiber Calcium Copper Iron Magnesium \ 0 0.900 0.000 . . . 0.008 14.100 0.082 0.027 1 7.800 0.000 . . . 99.500 0.034 0.100 8.500 0.000 2 0.800 0.100 0.000 0.000 0.000 3 1.500 0.000 0.097 41.200 0.097 0.096 4 1.200 0.000 22.200 0.072 0.008 1.200 717 0.500 0.000 15.800 0.400 0.600 24.800 . . . 718 0.034 0.062 0.089 0.000 0.000 0.099 719 0.400 0.400 0.000 5.500 0.056 1.600 720 1.800 1.100 2.600 0.200 0.300 0.000 721 0.500 0.300 0.000 0.500 0.008 0.200 Manganese Phosphorus Potassium Selenium Zinc Nutrition Density 0 1.300 0.091 15.5 19.100 0.039 7.070 1 0.088 117.300 129.2 0.054 0.700 130.100 2 0.000 0.000 0.0 0.000 0.000 5.400 3 4.000 5.196 0.024 30.8 43.800 0.035 4 0.098 22.800 37.1 0.034 0.053 27.007 717 0.040 13.900 42.6 0.034 0.700 24.249 718 0.500 0.015 3.2 10.800 0.096 0.433 719 1.727 2.500 0.060 25.0 53.000 0.069 720 0.092 92.900 313.0 0.015 0.500 9.400 721 2.700 0.055 18.0 63.000 0.048 1.804

[2395 rows x 35 columns]

Step 3: Check for missing values
missing_values = cleaned_data.isnull().sum()
print("\nMissing Values Summary:\n", missing_values)

 $\overline{\rightarrow}$ Missing Values Summary: food 0 Caloric Value 27 55 Fat Saturated Fats 0 0 Monounsaturated Fats Polyunsaturated Fats 0 0 Carbohydrates Sugars 11 Protein 0 Dietary Fiber 0 Cholesterol 0 Sodium 0 Water 0 Vitamin A 0 Vitamin B1 0 Vitamin B11 0 Vitamin B12 0 Vitamin B2 0 Vitamin B3 0 Vitamin B5 38 Vitamin B6 0

```
11/14/24, 12:38 AM
                                                                                                     psc project.jpynb - Colab
         Vitamin C
                                   0
         Vitamin D
                                   0
         Vitamin E
                                   0
         Vitamin K
                                   0
         Calcium
                                   0
                                   0
         Copper
         Iron
                                  11
         Magnesium
                                   0
         Manganese
                                   0
         Phosphorus
                                   0
                                   0
         Potassium
         Selenium
                                   0
                                   0
         Zinc
         Nutrition Density
                                   0
         dtype: int64
    cleaned data['Caloric Value'].fillna(cleaned data['Caloric Value'].mean(),inplace=True) #hanling missing values
          Show hidden output
    cleaned_data['Fat'].fillna(cleaned_data['Fat'].mean(),inplace=True) #hanling missing values
          Show hidden output
    cleaned_data['Sugars'].fillna(cleaned_data['Sugars'].mean(),inplace=True) #hanling missing values
    →
          Show hidden output
    cleaned_data['Vitamin B5'].fillna(cleaned_data['Vitamin B5'].mean(),inplace=True) #hanling missing values
          Show hidden output
    cleaned_data['Iron'].fillna(cleaned_data['Iron'].mean(),inplace=True) #hanling missing values
          Show hidden output
    #Check for missing values again
    missing_values = cleaned_data.isnull().sum()
    print("\nMissing Values Summary:\n", missing_values)
    \rightarrow
         Missing Values Summary:
          food
                                   0
         Caloric Value
                                 0
         Fat
         Saturated Fats
                                 0
                                 0
         Monounsaturated Fats
         Polyunsaturated Fats
                                 0
                                 0
         Carbohydrates
                                 0
         Sugars
```

11/14/24, 12:38 AM

Protein 0 Dietary Fiber 0 Cholesterol 0 Sodium 0 0 Water Vitamin A 0 Vitamin B1 0 Vitamin B11 0 Vitamin B12 0 Vitamin B2 0 Vitamin B3 0 Vitamin B5 0 Vitamin B6 0 Vitamin C 0 Vitamin D 0 Vitamin E 0 Vitamin K 0 0 Calcium 0 Copper 0 Iron Magnesium 0 0 Manganese Phosphorus 0 Potassium 0 Selenium 0 Zinc 0 Nutrition Density 0

dtype: int64

cleaned_data.info()

<pr

Index: 2395 entries, 0 to 721

	columns (total 35 columns		
#	Column	Non-Null Count	Dtype
0	food	2395 non-null	object
1	Caloric Value	2395 non-null	float64
2	Fat	2395 non-null	float64
3	Saturated Fats	2395 non-null	float64
4	Monounsaturated Fats	2395 non-null	float64
5	Polyunsaturated Fats	2395 non-null	float64
6	Carbohydrates	2395 non-null	float64
7	Sugars	2395 non-null	float64
8	Protein	2395 non-null	float64
9	Dietary Fiber	2395 non-null	float64
10	Cholesterol	2395 non-null	float64
11	Sodium	2395 non-null	float64
12	Water	2395 non-null	float64
13	Vitamin A	2395 non-null	float64
14	Vitamin B1	2395 non-null	float64
15	Vitamin B11	2395 non-null	float64
16	Vitamin B12	2395 non-null	float64
17	Vitamin B2	2395 non-null	float64
18	Vitamin B3	2395 non-null	float64
19	Vitamin B5	2395 non-null	float64
20	Vitamin B6	2395 non-null	float64

→

```
21 Vitamin C
                               2395 non-null
                                              float64
      22 Vitamin D
                               2395 non-null
                                              float64
      23 Vitamin E
                               2395 non-null
                                              float64
      24 Vitamin K
                               2395 non-null
                                              float64
      25 Calcium
                               2395 non-null
                                              float64
                               2395 non-null
         Copper
                                              float64
      26
      27 Iron
                               2395 non-null
                                              float64
      28 Magnesium
                               2395 non-null
                                              float64
         Manganese
                               2395 non-null
                                              float64
      29
      30 Phosphorus
                               2395 non-null
                                              float64
                               2395 non-null
      31 Potassium
                                              float64
      32 Selenium
                               2395 non-null
                                              float64
      33 Zinc
                               2395 non-null
                                              float64
      34 Nutrition Density
                               2395 non-null float64
     dtypes: float64(34), object(1)
     memory usage: 673.6+ KB
# Step 5: Standardize column names (convert to lowercase and replace spaces with underscores)
cleaned data.columns = cleaned data.columns.str.capitalize().str.replace(' ', ' ')
#cleaned data['Food'] = cleaned data['Food'].str.capitalize()
print(cleaned data.head())
                                        Caloric_value
                                                             Fat Saturated fats \
                                   Food
     0
                           cream cheese
                                                 51.0
                                                        5.000000
                                                                             2.9
     1
                      neufchatel cheese
                                                 215.0 19.400000
                                                                            10.9
       requeijao cremoso light catupiry
                                                 49.0 10.130935
                                                                             2.3
                         ricotta cheese
                                                  30.0
                                                        2.000000
                                                                             1.3
     4
                   cream cheese low fat
                                                  30.0
                                                       2.300000
                                                                             1.4
        Monounsaturated fats Polyunsaturated fats Carbohydrates Sugars Protein
                                            0.200
                                                                  0.500
     0
                        1.3
                                                            0.8
                                                                             0.9
                        4.9
     1
                                            0.800
                                                            3.1
                                                                  2.700
                                                                             7.8
     2
                        0.9
                                            0.000
                                                            0.9
                                                                  3.400
                                                                             0.8
                        0.5
     3
                                            0.002
                                                            1.5
                                                                  0.091
                                                                             1.5
                        0.6
                                            0.042
                                                            1.2
                                                                  0.900
     4
                                                                             1.2
        Dietary fiber ... Calcium
                                                  Magnesium Manganese \
                                   Copper
                                            Iron
     0
                 0.0 ...
                             0.008
                                   14.100
                                           0.082
                                                      0.027
                                                                 1.300
     1
                 0.0 ...
                            99.500
                                     0.034
                                           0.100
                                                      8.500
                                                                 0.088
     2
                 0.1 ...
                             0.000
                                     0.000
                                           0.000
                                                      0.000
                                                                 0.000
     3
                 0.0 ...
                             0.097 41.200
                                           0.097
                                                      0.096
                                                                 4.000
     4
                 0.0 ...
                            22.200
                                     0.072 0.008
                                                      1.200
                                                                 0.098
        Phosphorus Potassium Selenium
                                         Zinc Nutrition density
            0.091
                                19.100
                                                          7.070
     0
                        15.5
                                       0.039
     1
          117.300
                       129.2
                                 0.054
                                       0.700
                                                        130.100
     2
            0.000
                         0.0
                                 0.000
                                       0.000
                                                          5.400
     3
            0.024
                                                          5.196
                        30.8
                                43.800
                                       0.035
           22.800
                        37.1
                                 0.034 0.053
                                                         27.007
     [5 rows x 35 columns]
# Save the cleaned data to a new CSV file
```

https://colab.research.google.com/drive/15IEBRVjJum941vTmyh9MFVdUuk-kS5qP#scrollTo=jiJRewYt4b6d&printMode=true

#cleaned_data.to_csv(r"//content/drive/MyDrive/minor-/new.csv", index=False)

```
import pandas as pd
data = pd.read csv("/content/drive/MyDrive/minor-/new.csv")
non veg keywords = [
    'chicken', 'meat', 'fish', 'beef', 'mutton', 'egg', 'pork', 'lamb', 'shrimp',
    'turkey', 'crab', 'duck', 'bacon', 'ham', 'sausage', 'salami', 'lobster',
    'prawns', 'squid', 'octopus', 'veal', 'goat', 'quail', 'venison', 'foie gras',
    'oyster', 'scallop', 'clam', 'anchovy', 'tuna', 'salmon', 'sardine', 'caviar',
    'goose', 'kangaroo', 'boar', 'pepperoni', 'meatball', 'kebab', 'pastrami',
    'hot dog', 'prosciutto', 'jerky', 'escargot', 'tripe', 'liver', 'kidney',
    'giblets', 'bison', 'buffalo', 'rabbit', 'elk', 'frog', 'snail', 'conch',
    'cod', 'herring', 'halibut', 'swordfish', 'snapper', 'bass', 'flounder',
    'tilapia', 'mussels', 'calamari', 'eel', 'shark', 'alligator', 'ostrich',
    'reindeer', 'pheasant', 'squab', 'rattlesnake', 'turtle', 'roe', 'sea bass',
    'monkfish', 'pike', 'catfish', 'walleye', 'mahi mahi', 'grouper', 'haddock',
    'chorizo', 'salpicao', 'mortadella', 'serrano', 'chicken wings', 'ribs',
    'ox', 'trout', 'carp', 'partridge', 'moose', 'emu', 'iguana', 'wild boar',
    'black pudding', 'blood sausage', 'sweetbreads', 'bone marrow', 'head cheese'
def categorize_food(food_name):
    if isinstance(food name, str):
        food name lower = food name.lower()
        if any(keyword in food name lower for keyword in non veg keywords):
            return 'Non-Vegetarian'
    return 'Vegetarian'
data['Category'] = data['Food'].apply(categorize food)
# Display the updated dataset
print(data.head())
 <del>_</del>_₹
                                    Food Caloric value
                                                               Fat Saturated fats \
     9
                            cream cheese
                                                   51.0 5.000000
                                                                               2.9
                       neufchatel cheese
                                                  215.0 19.400000
                                                                              10.9
     2
        requeijao cremoso light catupiry
                                                   49.0 10.130935
                                                                               2.3
                          ricotta cheese
                                                   30.0
                                                          2.000000
                                                                               1.3
     3
     4
                    cream cheese low fat
                                                   30.0
                                                         2.300000
                                                                               1.4
        Monounsaturated fats Polyunsaturated_fats Carbohydrates Sugars Protein \
     9
                         1.3
                                             0.200
                                                              0.8
                                                                    0.500
                                                                               0.9
     1
                         4.9
                                             0.800
                                                              3.1
                                                                   2.700
                                                                               7.8
     2
                         0.9
                                             0.000
                                                              0.9
                                                                   3.400
                                                                               0.8
```

```
3
                        0.5
                                            0.002
                                                             1.5 0.091
                                                                              1.5
     4
                        0.6
                                            0.042
                                                             1.2
                                                                   0.900
                                                                              1.2
        Dietary fiber ... Copper Iron Magnesium Manganese Phosphorus \
     9
                 0.0 ... 14.100
                                   0.082
                                              0.027
                                                         1.300
                                                                     0.091
                 0.0 ... 0.034
                                   0.100
                                              8.500
                                                         0.088
                                                                   117.300
     1
     2
                 0.1 ... 0.000
                                   0.000
                                              0.000
                                                         0.000
                                                                     0.000
     3
                 0.0 ... 41.200
                                   0.097
                                              0.096
                                                         4.000
                                                                     0.024
                 0.0 ... 0.072
                                   0.008
                                              1.200
                                                         0.098
                                                                    22.800
        Potassium Selenium
                            Zinc Nutrition density
                                                        Category
     0
            15.5
                    19.100 0.039
                                               7.070
                                                      Vegetarian
     1
           129.2
                     0.054 0.700
                                             130.100
                                                      Vegetarian
     2
             0.0
                     0.000 0.000
                                               5.400 Vegetarian
     3
             30.8
                    43.800 0.035
                                               5.196 Vegetarian
             37.1
                     0.034 0.053
                                              27.007 Vegetarian
     [5 rows x 36 columns]
import matplotlib.pyplot as plt
def get user input():
    print("Welcome to the Food Recommendation System!")
    has disease = input("Do you have any special disease? Press 1 for Yes, Press 2 for No: ").strip()
    diseases = [
        "Diabetes", "Hypertension (High Blood Pressure)", "Obesity", "Heart Disease (Cardiovascular Disease)",
        "Asthma", "Chronic Obstructive Pulmonary Disease (COPD)", "Cancer", "Stroke", "Alzheimer's Disease",
        "Parkinson's Disease", "Arthritis (Osteoarthritis/Rheumatoid Arthritis)", "Chronic Kidney Disease",
        "Hepatitis (A, B, C)", "HIV/AIDS", "Influenza (Flu)", "Pneumonia", "Tuberculosis (TB)", "Malaria",
        "Dementia", "Irritable Bowel Syndrome (IBS)", "Epilepsy", "Migraine", "Gastritis", "Celiac Disease",
        "Lupus", "Thyroid Disorders (Hypothyroidism/Hyperthyroidism)", "Gout", "Multiple Sclerosis (MS)",
        "Psoriasis", "Eczema"
    disease = None
    if has disease == '1':
        print("\nSelect your disease from the list below:")
        for idx, d in enumerate(diseases, start=1):
            print(f"{idx}: {d}")
        disease choice = int(input("Enter the number corresponding to your disease: ").strip())
        if 1 <= disease choice <= len(diseases):</pre>
            disease = diseases[disease_choice - 1]
        else:
            print("Invalid choice, proceeding without specific disease.")
    vegetarian = input("\nAre you vegetarian? (yes/no): ").strip().lower() == 'yes'
    nutrients = nutrients = [
    "Caloric value", "Fat", "Saturated fats", "Monounsaturated fats", "Polyunsaturated fats",
```

```
"Carbohydrates", "Sugars", "Protein", "Dietary_fiber", "Cholesterol", "Sodium", "Water",
    "Vitamin a", "Vitamin b1", "Vitamin b11", "Vitamin b12", "Vitamin b2", "Vitamin b3",
    "Vitamin b5", "Vitamin b6", "Vitamin c", "Vitamin d", "Vitamin e", "Vitamin k",
    "Calcium", "Copper", "Iron", "Magnesium", "Manganese", "Phosphorus", "Potassium",
    "Selenium", "Zinc"
    print("\nSelect up to 3 nutrient deficiencies from the list below:")
    for idx, n in enumerate(nutrients, start=1):
        print(f"{idx}: {n}")
    deficiencies = []
    while len(deficiencies) < 3:
        try:
            choice = int(input(f"Enter the number corresponding to deficiency {len(deficiencies)+1} (or 0 to stop): ").strip())
            if choice == 0:
                break
            if 1 <= choice <= len(nutrients):</pre>
                deficiencies.append(nutrients[choice - 1])
            else:
                print("Invalid choice, try again.")
        except ValueError:
            print("Please enter a valid number.")
    print("\nWhat is your primary health goal? (Choose one)")
    print("Options: muscle gain, weight loss, overall health")
    health_goal = input("Your choice: ").strip().lower()
    user data = {
        'disease': disease,
        'vegetarian': vegetarian,
        'deficiencies': deficiencies,
        'health_goal': health_goal
    return user_data
user_input = get_user_input()
print("\nUser Input Summary:")
print(f"Disease: {user input['disease']}")
print(f"Vegetarian: {user_input['vegetarian']}")
print(f"Nutrient Deficiencies: {', '.join(user_input['deficiencies'])}")
print(f"Health Goal: {user_input['health_goal']}")
food_data=data.copy()
def apply_disease_criteria(food_data, disease):
```

```
disease conditions = {
        "Diabetes": (food data['Sugars'] < 5) & (food data['Carbohydrates'] < 60) & (food data['Dietary fiber'] > 5),
        "Hypertension (High Blood Pressure)": (food data['Sodium'] < 300) & (food data['Potassium'] > 200),
        "Obesity": (food data['Caloric value'] < 400) & (food data['Dietary fiber'] > 5) & (food data['Protein'] > 20),
        "Heart Disease (Cardiovascular Disease)": (food data['Saturated fats'] < 3) & (food data['Cholesterol'] < 50) & (food data['Sodium'] < 300) & (food data['Dietary fiber'] > 5),
        "Asthma": (food data['Vitamin c'] > 15) & (food data['Vitamin e'] > 2) & (food data['Saturated fats'] < 3),
        "Chronic Obstructive Pulmonary Disease (COPD)": (food data['Dietary fiber'] < 5) & (food data['Caloric value'] > 400),
        "Cancer": (food data['Vitamin a'] > 300) & (food data['Vitamin c'] > 20) & (food data['Dietary fiber'] > 5),
        "Stroke": (food_data['Potassium'] > 300) & (food_data['Sodium'] < 300),
        "Alzheimer's Disease": (food data['Vitamin e'] > 2) & (food data['Saturated fats'] < 3),
        "Parkinson's Disease": (food data['Protein'] > 15) & (food data['Vitamin b12'] > 2)
    if disease in disease conditions:
        return food_data.loc[disease_conditions[disease]]
    else:
        return food data
disease=user input['disease']
filtered data = apply disease criteria(food data, disease)
def apply veg nonveg preference(filtered data, vegetarian preference):
    if vegetarian_preference:
        filtered data = filtered data[filtered data['Category'].str.lower() == 'vegetarian']
    else:
        filtered data = filtered data[filtered data['Category'].str.lower() == 'non-vegetarian']
    return filtered data
vegetarian preference=user input['vegetarian']
filtered foods = apply veg nonveg preference(filtered data, vegetarian preference)
def apply_nutrient_deficiency(filtered_data, deficiencies):
    deficiency conditions = {
        "Caloric Value": filtered_data['Caloric_value'] > filtered_data['Caloric_value'].median(),
        "Fat": filtered_data['Fat'] > filtered_data['Fat'].median(),
        "Saturated Fats": filtered data['Saturated fats'] > filtered data['Saturated fats'].median(),
```

```
"Monounsaturated Fats": filtered data['Monounsaturated fats'] > filtered data['Monounsaturated fats'].median().
        "Polyunsaturated Fats": filtered data['Polyunsaturated fats'] > filtered data['Polyunsaturated fats'].median(),
        "Carbohydrates": filtered data['Carbohydrates'] > filtered data['Carbohydrates'].median(),
        "Sugars": filtered data['Sugars'] > filtered data['Sugars'].median(),
        "Protein": filtered data['Protein'] > filtered data['Protein'].median(),
        "Dietary Fiber": filtered data['Dietary fiber'] > filtered data['Dietary fiber'].median().
        "Cholesterol": filtered data['Cholesterol'] > filtered data['Cholesterol'].median(),
        "Sodium": filtered data['Sodium'] > filtered data['Sodium'].median(),
        "Water": filtered data['Water'] > filtered data['Water'].median(),
        "Vitamin A": filtered data['Vitamin a'] > filtered data['Vitamin a'].median(),
        "Vitamin B1": filtered data['Vitamin b1'] > filtered data['Vitamin b1'].median(),
        "Vitamin B11": filtered data['Vitamin b11'] > filtered data['Vitamin b11'].median(),
        "Vitamin B12": filtered data['Vitamin b12'] > filtered data['Vitamin b12'].median(),
        "Vitamin B2": filtered data['Vitamin b2'] > filtered data['Vitamin b2'].median(),
        "Vitamin B3": filtered_data['Vitamin_b3'] > filtered_data['Vitamin_b3'].median(),
        "Vitamin B5": filtered data['Vitamin b5'] > filtered data['Vitamin b5'].median(),
        "Vitamin B6": filtered data['Vitamin b6'] > filtered data['Vitamin b6'].median(),
        "Vitamin C": filtered data['Vitamin c'] > filtered data['Vitamin c'].median(),
        "Vitamin D": filtered_data['Vitamin_d'] > filtered_data['Vitamin_d'].median(),
        "Vitamin E": filtered data['Vitamin e'] > filtered data['Vitamin e'].median(),
        "Vitamin K": filtered data['Vitamin k'] > filtered data['Vitamin k'].median(),
        "Calcium": filtered data['Calcium'] > filtered data['Calcium'].median(),
        "Copper": filtered data['Copper'] > filtered data['Copper'].median(),
        "Iron": filtered data['Iron'] > filtered data['Iron'].median(),
        "Magnesium": filtered data['Magnesium'] > filtered data['Magnesium'].median(),
        "Manganese": filtered data['Manganese'] > filtered data['Manganese'].median(),
        "Phosphorus": filtered data['Phosphorus'] > filtered_data['Phosphorus'].median(),
        "Potassium": filtered data['Potassium'] > filtered data['Potassium'].median(),
        "Selenium": filtered_data['Selenium'] > filtered_data['Selenium'].median(),
        "Zinc": filtered data['Zinc'] > filtered data['Zinc'].median()
    combined condition = pd.Series([False] * len(filtered data), index=filtered data.index)
    for deficiency in deficiencies:
        if deficiency in deficiency conditions:
            combined condition |= deficiency conditions[deficiency]
    return filtered data[combined condition]
deficiencies = user_input['deficiencies']
filtered data = apply nutrient deficiency(filtered data, deficiencies)
health goal = user input['health goal']
def apply health goal(filtered data, health goal):
    health_goal_conditions = {
        "muscle gain": (filtered data['Protein'] > filtered data['Protein'].median()) &
                       (filtered data['Fat'] > filtered data['Fat'].quantile(0.25)),
        "weight loss": (filtered_data['Fat'] < filtered_data['Fat'].quantile(0.25)) &
                       (filtered data['Dietary fiber'] > filtered data['Dietary fiber'].median()) &
```

```
(filtered data['Caloric value'] < filtered data['Caloric value'].median()),</pre>
        "overall health": (filtered data['Vitamin a'] > filtered data['Vitamin a'].median()) &
                          (filtered data['Vitamin c'] > filtered data['Vitamin c'].median()) &
                          (filtered_data['Calcium'] > filtered_data['Calcium'].median()) &
                          (filtered data['Potassium'] > filtered data['Potassium'].median()) &
                          (filtered data['Dietary fiber'] > filtered data['Dietary fiber'].median())
    # Apply the condition based on the selected health goal
    if health goal in health goal conditions:
        return filtered data.loc[health goal conditions[health goal]]
    else:
        print(f"Unknown health goal: {health_goal}. Returning unfiltered data.")
        return filtered data
filtered_foods = apply_health_goal(filtered_foods, user_input['health_goal']).head(10)
from tabulate import tabulate
table = tabulate(filtered foods, headers='keys', tablefmt='grid')
print(table)
def plot food deficiencies(filtered foods, deficiencies):
    for deficiency in deficiencies:
        if deficiency in filtered foods.columns:
            plt.figure(figsize=(10, 6))
            plt.bar(filtered_foods['Food'], filtered_foods[deficiency], color='skyblue')
            plt.title(f'{deficiency} Levels in Recommended Foods')
            plt.xlabel('Food')
            plt.ylabel(f'{deficiency} Level')
            plt.xticks(rotation=45, ha='right')
            plt.tight layout()
            plt.show()
        else:
            print(f"Deficiency {deficiency} not found in dataset columns.")
```

plot_food_deficiencies(filtered_foods, deficiencies)

11/14/24, 12:38 AM psc_project.ipynb - Colab

New Section

- I. DIADELES
- 2: Hypertension (High Blood Pressure)
- 3: Obesity
- 4: Heart Disease (Cardiovascular Disease)
- 5: Asthma
- 6: Chronic Obstructive Pulmonary Disease (COPD)
- 7: Cancer
- 8: Stroke
- 9: Alzheimer's Disease
- 10: Parkinson's Disease
- 11: Arthritis (Osteoarthritis/Rheumatoid Arthritis)
- 12: Chronic Kidney Disease
- 13: Hepatitis (A, B, C)
- 14: HIV/AIDS
- 15: Influenza (Flu)
- 16: Pneumonia
- 17: Tuberculosis (TB)
- 18: Malaria
- 19: Dementia
- 20: Trritable Bowel Syndrome (TRS)