```
import pandas as pd
import numpy as np
from tabulate import tabulate
import seaborn as sns
import matplotlib.pyplot as plt

# Load the dataset from the CSV file
dataset = pd.read_csv('/content/heart_attack_prediction_dataset.csv')
continentcsv = pd.read_csv('continent.csv')
df = pd.read_csv('heart_attack_prediction_dataset.csv')
names= pd.read_csv('/content/names.csv')
```

New Section

Phase 1

```
# List of columns to analyze
columns_to_analyze = [
    'Age', 'Sex', 'Cholesterol', 'Blood Pressure', 'Heart Rate', 'Diabetes',
    'Family History', 'Smoking', 'Obesity', 'Alcohol Consumption',
    'Exercise Hours Per Week', 'Diet', 'Previous Heart Problems', 'Medication Use',
    'Stress Level', 'Sedentary Hours Per Day', 'Income', 'BMI', 'Triglycerides',
    'Physical Activity Days Per Week', 'Sleep Hours Per Day', 'Country',
    'Continent', 'Hemisphere', 'Heart Attack Risk'
]
# Create a dictionary to store information for each column
column_info = {'Name of data': [], 'Type of data': [], 'Range of data': [],
               'Min': [], 'Max': [], 'Mean': [], 'Mode': [], 'Median': [], 'Outliers': []}
# Analyze each column
for column_name in columns_to_analyze:
    column_data = dataset[column_name]
    data_type = column_data.dtype
    if pd.api.types.is_numeric_dtype(data_type):
        data_summary = column_data.describe()
        mode_value = column_data.mode().values[0]
        median_value = column_data.median()
        Q1 = column_data.quantile(0.25)
        Q3 = column_data.quantile(0.75)
        IOR = 03 - 01
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        outliers = column_data[(column_data < lower_bound) | (column_data > upper_bound)]
        # Add information to the dictionary
        column_info['Name of data'].append(column_name)
        column_info['Type of data'].append(data_type)
        column_info['Range of data'].append(f"{column_data.min()} - {column_data.max()}")
        column_info['Min'].append(column_data.min())
        column_info['Max'].append(column_data.max())
        column_info['Mean'].append(data_summary['mean'])
        column info['Mode'].append(mode value)
        column_info['Median'].append(median_value)
        column_info['Outliers'].append(', '.join(map(str, outliers.tolist())))
        mode_value = column_data.mode().values[0]
        range_value = column_data.unique()
        # For non-numeric columns, provide some basic information
        column_info['Name of data'].append(column_name)
        column_info['Type of data'].append(data_type)
        column_info['Range of data'].append(range_value)
        column_info['Min'].append('Not applicable')
        column_info['Max'].append('Not applicable')
        column_info['Mean'].append('Not applicable')
        column_info['Mode'].append(mode_value)
        column_info['Median'].append('Not applicable')
        column info['Outliers'].append('Not applicable')
# Create a table
table = {key: column_info[key] for key in column_info.keys()}
# Display the results in a table
print(tabulate(table, headers='keys', tablefmt='pretty'))
```

	_+		_+
Name of data Type of data		Range of data	Min
Age	float64	18.0 - 230.0	18.0
Sex	object	['Male' 'x' 'Female' nan]	Not applicabl
Cholesterol	float64	120.0 - 400.0	120.0
Blood Pressure	object	['158/88' '165/93' '174/99' '137/94' '94/76' '119/67']	Not applicabl
Heart Rate	float64	40.0 - 110.0	40.0
Diabetes	int64	0 - 1	0
Family History	int64	0 - 1	0
Smoking	int64	0 - 1	0
Obesity	int64	0 - 1	0
Alcohol Consumption	int64	0 - 1	0
Exercise Hours Per Week	float64	0.002442348 - 19.99870905	0.002442348

data mining project.ipynb - Colaboratory

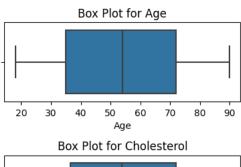
		3	
Diet	object	['Average' 'Unhealthy' 'Healthy']	Not applicabl
Previous Heart Problems int64		0 - 1	0
Medication Use int64		0 - 1	0
Stress Level int64		1 - 10	1
Sedentary Hours Per Day	float64	0.001263206 - 11.99931341	0.001263206
Income	int64	20062 - 299954	20062
BMI float64		18.00233658 - 39.99721082	18.00233658
Triglycerides int64		30 - 800	30
ysical Activity Days Per Week int64		0 - 7	0
Sleep Hours Per Day int64		4 - 10	4
Country	object	['Argentina' 'Canada' 'France' 'Thailand' 'Germany' 'Japan' 'Brazil'	Not applicabl
		'South Africa' 'United States' 'Vietnam' 'China' 'Italy' 'Spain' 'India'	
		'Nigeria' 'New Zealand' 'South Korea' 'Australia' 'Colombia'	
		'United Kingdom']	
Continent	object	['South America' 'North America' 'Europe' 'Asia' 'Africa' 'Australia']	Not applicabl
Hemisphere object		['Southern Hemisphere' 'Northern Hemisphere']	Not applicabl
Heart Attack Risk	int64	0 - 1	0
	+		+

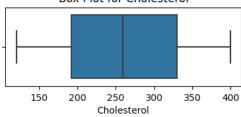
```
# Identify numeric columns
numeric_columns = dataset.select_dtypes(include=['number']).columns

# Set up subplots
fig, axes = plt.subplots(nrows=len(numeric_columns), figsize=(4, 2 * len(numeric_columns)))

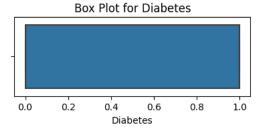
# Create box plots for each numeric column
for i, column_name in enumerate(numeric_columns):
    sns.boxplot(x=dataset[column_name], ax=axes[i])
    axes[i].set_title(f'Box Plot for {column_name}')

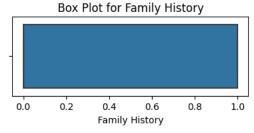
# Adjust layout
plt.tight_layout()
plt.show()
```

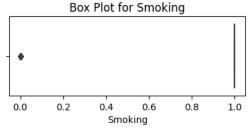


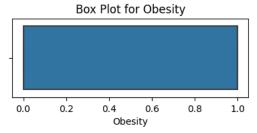




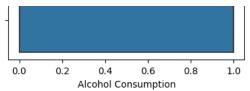








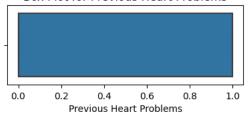




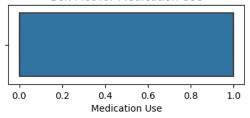
Box Plot for Exercise Hours Per Week



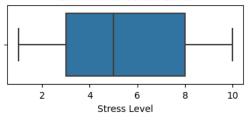
Box Plot for Previous Heart Problems



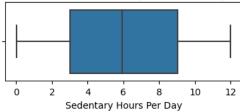
Box Plot for Medication Use



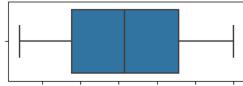
Box Plot for Stress Level



Box Plot for Sedentary Hours Per Day



Box Plot for Income



50000 100000 150000 200000 250000 300000 Income

Box Plot for BMI



3

4

1

1

1

1

1

1

```
20
                      25
                                         35
                                                   40
                               30
                             BMI
                 Box Plot for Triglycerides
Phase 1 part 3
                                                    1 1
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# Select relevant features
selected_features = ['Age', 'Exercise Hours Per Week', 'Physical Activity Days Per Week', 'Stress Level']
# Drop rows with missing values in selected features
df_selected = df[selected_features + ['Heart Attack Risk']].dropna()
# Define criteria for a healthy lifestyle (you can adjust these criteria)
healthy_criteria = ((df_selected['Age'] < 40) &</pre>
                    (df_selected['Exercise Hours Per Week'] >= 3) &
                    (df_selected['Physical Activity Days Per Week'] >= 4) &
                    (df_selected['Stress Level'] <= 3))</pre>
# Add a column indicating whether the person is living a healthy life
df_selected['Healthy Lifestyle'] = healthy_criteria.astype(int)
# Split the dataset into features and target
X = df_selected[selected_features]
y = df_selected['Healthy Lifestyle']
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train a RandomForestClassifier
classifier = RandomForestClassifier(random_state=42)
{\tt classifier.fit(X\_train,\ y\_train)}
# Make predictions on the test set
y_pred = classifier.predict(X_test)
# Evaluate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
# Add the 'Healthy Lifestyle' column to the original dataset based on 'df_selected' Patient IDs
# df['Healthy Lifestyle'] = df.set_index('Patient ID').loc[df_selected.set_index('Patient ID').index]['Healthy Lifestyle'].values
df['healthy_criteria']=healthy_criteria
print(df)
# Display the updated dataset
# print(df['healthy_criteria'].sum())
     8759
             QSV6764
                       28.0 Female
                                              120
                                                         157/102
                                                                          73
     8760
             XKA5925
                       47.0
                               Male
                                              250
                                                          161/75
                                                                         105
     8761
             EPE6801
                       36.0
                               Male
                                              178
                                                          119/67
                                                                          60
     8762
             ZWN9666
                       25.0 Female
                                              356
                                                          138/67
                                                                          75
                                     Smoking
                                              Obesity
           Diabetes
                    Family History
                                                             Income
                                                                           BMI
     0
                                                                     31.251233
                  0
                                  0
                                            1
                                                     0
                                                        . . .
                                                             261404
                  1
                                  1
     1
                                            1
                                                     1
                                                             285768
                                                                     27.194973
                                                        . . .
                                                     0 ...
                  1
                                  0
                                            0
                                                             235282 28.176571
```

0

...

125640

160555

36,464704

21.809144

ī	235 507		1	/			
2	587		4	4			
3 4	378		3 1	4 5			
4	231						
8758	67		7	7			
8759	617		4	9			
8760	527		4	4			
8761	114		2	8			
8762	180		7	4			
0/02	100		/	4			
	Country	Continent	Hemisphere	Heart Attack Risk \			
0	Argentina	South America	Southern Hemisphere	0			
1	Canada	North America	Northern Hemisphere	0			
2	France	Europe	Northern Hemisphere	0			
3	Canada	North America	Northern Hemisphere	0			
4	Thailand	Asia	Northern Hemisphere	0			
• • •	• • •	• • •	• • •	•••			
8758	Thailand	Asia	Northern Hemisphere				
8759	Canada	North America	Northern Hemisphere				
8760	Brazil	South America	Southern Hemisphere				
8761	Brazil	South America					
8762	United Kingdom	Europe	Northern Hemisphere	1			
	healthy_criteri	.a					
0	Fals						
1	False						
2	False						
3	NaN						
4	False						
• • •							
8758	Fals						
8759	Fals						
8760	Fals						
8761							
8762	False						
[8763 rows x 27 columns]							

Phase 2 Part 1

```
# Create a table to store the results
table_data = []
# Validation function for 'Patient ID'
def validate_patient_id(patient_id):
    pattern = re.compile(r'^[A-Za-z]{3}\d{4}$')
    return bool(pattern.match(str(patient_id)))
# Check the uniqueness of 'Patient ID'
is_unique = df['Patient ID'].nunique() / len(df)
# Find non-unique 'Patient IDs'
non unique patient ids = df[df.duplicated(subset='Patient ID', keep=False)]['Patient ID']
# Attribute: 'Patient ID'
column name = 'Patient ID'
# Number of Data
num_data = len(df)
num_null = df[column_name].isnull().sum()
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_patient_id).sum() / num_data) * 100 if num_data > 0 else None
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Consistency (Uniqueness)
consistency = is_unique * 100
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", "-", f"{completeness:.2f}\%", f"{consistency:.2f}\%", "-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Display the result table using tabulate for a nice format
#print(tabulate(result_table, headers='keys', tablefmt='pretty'))
# Print non-unique 'Patient IDs'
#print("\nNon-unique Patient IDs:")
#print(non_unique_patient_ids)
# Validation function for 'Age'
def validate_age(age):
    return 0 <= age <= 150 if pd.notna(age) else None
# Attribute: 'Age'
column_name = 'Age'
# Number of Data
num_data = df[column_name].count()
# Null
num null = df[column name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_age).sum() / num_data) * 100 if num_data > 0 else None
accuracy_series = df['Age'].apply(lambda x: 0 <= x <= 150 if pd.notna(x) else None)</pre>
accuracy = accuracy_series.all()
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table_data.append([column_name, num_data, num_null, f"{validity:.2f}%", f"{accuracy_percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Print rows where 'Age' does not match the criteria
#invalid_age_rows = df[~df['Age'].apply(validate_age)]
#print("\nRows where 'Age' does not match the criteria:")
#print(tabulate(invalid_age_rows, headers='keys', tablefmt='pretty'))
# Validation function for 'Sex'
def validate sex(sex):
    return sex.lower() in ['male', 'female'] if pd.notna(sex) else None
# Attribute: 'Sex'
column_name = 'Sex'
# Number of Data
num_data = df[column_name].count()
# Null
num null = df[column name].isnull().sum()
# Completeness
```

```
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_sex).sum() \ / \ num_data) \ * \ 100 \ if \ num_data \ > \ 0 \ else \ None
# Accuracy
accuracy_series = df['Sex'].apply(lambda x: x.lower() in ['male', 'female'] if pd.notna(x) else None)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table_data.append([column_name, num_data, num_null, f"{validity:.2f}%", f"{accuracy_percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Print rows where 'Sex' does not match the criteria
#invalid_sex_rows = df[~df['Sex'].apply(validate_sex)]
#print("\nRows where 'Sex' does not match the criteria:")
#print(tabulate(invalid_sex_rows, headers='keys', tablefmt='pretty'))
# Accurate function for 'Blood Pressure'
def accurate_blood_pressure(blood_pressure):
       if pd.notna(blood_pressure):
              parts = blood_pressure.split('/')
               if len(parts) == 2:
                      try:
                             x, y = map(int, parts)
                             return x > y
                      except ValueError:
                             return False
       return False
# Validation function for 'Blood Pressure'
def validate_blood_pressure(blood_pressure):
       if pd.notna(blood pressure):
              parts = blood_pressure.split('/')
              if len(parts) == 2:
                    return True
       return False
# Attribute: 'Blood Pressure'
column name = 'Blood Pressure'
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_blood_pressure).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df['Blood Pressure'].apply(accurate_blood_pressure)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"\{validity:.2f\}\%", f"\{accuracy\_percentage:.2f\}\%", f"\{completeness:.2f\}\%", f"[validity:.2f\}\%", f"[accuracy\_percentage:.2f]\%", f"[completeness:.2f]\%", f"[validity:.2f]\%", f"[accuracy\_percentage:.2f]\%", f"[completeness:.2f]\%", f"[completeness
# Create a DataFrame from the table data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
```

```
column_names = ['Diabetes','Previous Heart Problems','Family History','Smoking','Obesity','Alcohol Consumption','Medication Use','Heart Atta
for column_name in column_names:
    def validate_pre(pre):
        return 0 <= pre <= 1 if pd.notna(pre) else None
    def accurate_pre(pre):
        return 0 <= pre <= 1 if pd.notna(pre) else None
# Number of Data</pre>
```

```
num_data = df[column_name].count()
    # Nu11
    num_null = df[column_name].isnull().sum()
    # Completeness
    completeness = (1 - (num_null / num_data)) * 100
    # Validity based on the specified pattern
    validity = (df[column_name].apply(validate_pre).sum() / num_data) * 100 if num_data > 0 else None
    # Accuracy
    accuracy_series = df[column_name].apply(accurate_pre)
    # Accuracy Percentage
    accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
    # Append the results to the table_data list
    table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%", f"{completeness:.2f}\%", f"{completeness:.2f}\%
    # Create a DataFrame from the table data list
    result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness"
def validate_str(pre):
         return 1 <= pre <= 10 if pd.notna(pre) else None
def accurate_str(pre):
         return 1 <= pre <= 10 if pd.notna(pre) else None
column_name = "Stress Level"
# Number of Data
num_data = df[column_name].count()
# Null
num null = df[column name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_str).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df[column_name].apply(accurate_str)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table_data.append([column_name, num_data, num_null, f"{validity:.2f}%", f"{accuracy_percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_sed(pre):
        return 0 <= pre <= 24 if pd.notna(pre) else None
def accurate_sed(pre):
         return 0 <= pre <= 24 if pd.notna(pre) else None
column_name = "Sedentary Hours Per Day"
# Number of Data
num data = df[column name].count()
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_sed).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy series = df[column name].apply(accurate sed)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%", f"{completeness:.2f}\%", f"{completeness:.2f}\%
# Create a DataFrame from the table data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_in(inc):
        return 0 <= inc if pd.notna(inc) else None
def accurate_in(inc):
         return 0 <= inc if pd.notna(inc) else None
column name = "Income"
# Number of Data
num_data = df[column_name].count()
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
```

```
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_in).sum() / num_data) * 100 if num_data > 0 else None
accuracy_series = df[column_name].apply(accurate_in)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"\{validity:.2f\}\%", f"\{accuracy\_percentage:.2f\}\%", f"\{completeness:.2f\}\%", f"\{completeness:.2f\}\%
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate bmi(bmi):
         return 0 <= bmi if pd.notna(bmi) else None
def accurate_bmi(bmi):
         return 9 <= bmi <= 105 if pd.notna(bmi) else None
column_name = "BMI"
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_bmi).sum() / num_data) * 100 if num_data > 0 else None
accuracy_series = df[column_name].apply(accurate_bmi)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table data list
table data.append([column name, num data, num null, f"{validity:.2f}%", f"{accuracy percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_T(bmi):
         return 0 <= bmi if pd.notna(bmi) else None
def accurate_T(bmi):
         return 0 <= bmi if pd.notna(bmi) else None
column_name = "Triglycerides"
# Number of Data
num_data = df[column_name].count()
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num null / num data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_T).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df[column_name].apply(accurate_T)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%", f"{completeness:.2f}\%", f"{completeness:.2f}\%
# Create a DataFrame from the table data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_P(bmi):
         return 0 <= bmi <= 7 if pd.notna(bmi) else None
def accurate_P(bmi):
        return 0 <= bmi <= 7 if pd.notna(bmi) else None
column_name = "Physical Activity Days Per Week"
# Number of Data
num_data = df[column_name].count()
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_P).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df[column_name].apply(accurate_P)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
```

```
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%",f"{completeness:.2f}\%",-",-"])
# Create a DataFrame from the table data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_S(bmi):
         return 0 <= bmi <= 24 if pd.notna(bmi) else None
def accurate_S(bmi):
        return 0 <= bmi <= 24 if pd.notna(bmi) else None
column_name = "Sleep Hours Per Day"
# Number of Data
num_data = df[column_name].count()
# Null
num null = df[column name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column\_name].apply(validate\_S).sum() \ / \ num\_data) * 100 \ if \ num\_data > 0 \ else \ None \ (e.s.) \ (e.s.) \ (f.s.) \
accuracy_series = df[column_name].apply(accurate_S)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table_data.append([column_name, num_data, num_null, f"{validity:.2f}%", f"{accuracy_percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_C(bmi):
        return 0 <= len(bmi) <= 90 if pd.notna(bmi) else None
def accurate_C(bmi):
        return 3 <= len(bmi) <= 56 if pd.notna(bmi) else None
column_name = "Country"
# Number of Data
num_data = df[column_name].count()
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_C).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df[column_name].apply(accurate_C)
# Accuracy Percentage
{\tt accuracy\_percentage = (accuracy\_series.sum() / num\_data) * 100 if num\_data > 0 else None}
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%", f"{completeness:.2f}\%", f"{completeness:.2f}\%
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_con(bmi):
        return bmi in ['Europe', 'Australia', 'Asia', 'Africa', 'North America', 'South America'] if pd.notna(bmi) else None
def accurate_con(bmi):
        return bmi in ['Europe', 'Australia', 'Asia', 'Africa', 'North America', 'South America'] if pd.notna(bmi) else None
column_name = "Continent"
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column\_name].apply(validate\_con).sum() \ / \ num\_data) * 100 \ if \ num\_data > 0 \ else \ None
# Accuracy
accuracy_series = df[column_name].apply(accurate_con)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"{validity:.2f}\%", f"{accuracy\_percentage:.2f}\%",f"{completeness:.2f}\%","-","-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
```

```
def validate hem(bmi):
          return bmi in ['Northern Hemisphere', 'Southern Hemisphere'] if pd.notna(bmi) else None
def accurate_hem(bmi):
          return bmi in ['Northern Hemisphere', 'Southern Hemisphere'] if pd.notna(bmi) else None
column name = "Hemisphere"
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_hem).sum() / num_data) * 100 if num_data > 0 else None
accuracy_series = df[column_name].apply(accurate_hem)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"\{validity:.2f\}\%", f"\{accuracy\_percentage:.2f\}\%", f"\{completeness:.2f\}\%", f"\{completeness:.2f\}\%
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Display the result table using tabulate for a nice format
print(tabulate(result_table, headers='keys', tablefmt='pretty'))
# Print rows where 'Blood Pressure' does not match the criteria
#invalid_blood_pressure_rows = df[~df['Blood Pressure'].apply(validate_blood_pressure)]
#print("\nRows where 'Blood Pressure' does not match the criteria:")
#print(tabulate(invalid_blood_pressure_rows, headers='keys', tablefmt='pretty'))
```

1	Name of the Attribute	Number of Data	Null	Validity	Accuracy	Completeness	Consistency	Currentness
0	Patient ID	+ 8763	 0	+ 99.93%	+ -	100.00%	+ 99.98%	+ -
1	Age	8761	2	99.99%	99.99%	99.98%	j -	j -
2	Sex	8760	3	99.99%	99.99%	99.97%	· -	j -
j 3	Blood Pressure	8763	0	100.00%	95.08%	100.00%	j -	j -
4	Diabetes	8763	0	100.00%	100.00%	100.00%	· -	j -
5	Previous Heart Problems	8763	0	100.00%	100.00%	100.00%	j -	j -
6	Family History	8763	0	100.00%	100.00%	100.00%	-	-
7	Smoking	8763	0	100.00%	100.00%	100.00%	-	-
8	Obesity	8763	0	100.00%	100.00%	100.00%	j -	-
9	Alcohol Consumption	8763	0	100.00%	100.00%	100.00%	-	-
10	Medication Use	8763	0	100.00%	100.00%	100.00%	-	-
11	Heart Attack Risk	8763	0	100.00%	100.00%	100.00%	-	-
12	Stress Level	8763	0	100.00%	100.00%	100.00%	-	-
13	Sedentary Hours Per Day	8763	0	100.00%	100.00%	100.00%	-	-
14	Income	8763	0	100.00%	100.00%	100.00%	-	-
15	BMI	8763	0	100.00%	100.00%	100.00%	-	-
16	Triglycerides	8763	0	100.00%	100.00%	100.00%	-	-
17	Physical Activity Days Per Week	8763	0	100.00%	100.00%	100.00%	-	-
18	Sleep Hours Per Day	8763	0	100.00%	100.00%	100.00%	-	-
19	Country	8763	0	100.00%	100.00%	100.00%	-	-
20	Continent	8763	0	100.00%	100.00%	100.00%	-	-
21	Hemisphere	8763	0	100.00%	100.00%	100.00%	-	-
	 	+	+	+	+	+	+	+

Patient Id validity 3 three letters and 4 digits Consistency unique Age validity 0 < Age accuracy 0 < x < 180 Sex validity Male and Female Cholesterol Blood Pressure validity format x/y x>yDiabetes Family-History Smoking Obesity Alcohol Consumption validity 0-1 Exercise Hours Per Week validity 0-168 Accuracy 0-100Diet validity Unhealthy - Average - Healthy Previous Heart Problems Medication Use validity 0-1 Stress Level validity 1-10 Sedentary Hours Per Day validity 0-24 income validity digits only BMI validity 0 < x Accuracy 9 < x < 105 Triglycerides validity 0 < x Physical Activity Days Per Week validity 0 <= x <= 7 Sleep Hours Per Day validity 0 <= x <= 24 Heart Attack Risk validity 0-1 x

```
import pandas as pd
from tabulate import tabulate

# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
```

```
dataset_path = '/content/heart_attack_prediction_dataset.csv
df = pd.read_csv(dataset_path)
# Select the numeric column for outlier removal
numeric_column = 'Age'
# Calculate quartiles and IQR
Q1 = df[numeric_column].quantile(0.25)
Q3 = df[numeric_column].quantile(0.75)
IQR = Q3 - Q1
# Calculate lower and upper bounds
lower\_bound = Q1 - 0.5 * IQR
upper_bound = Q3 + 0.5 * IQR
# Identify outliers
outliers = df[(df[numeric_column] < lower_bound) | (df[numeric_column] > upper_bound)]
# Display outliers in a table
outliers_table = tabulate(outliers, headers='keys', tablefmt='pretty')
print("Identified outliers:")
print(outliers_table)
# Remove outliers from the dataset
df_no_outliers = df[(df[numeric_column] >= lower_bound) & (df[numeric_column] <= upper_bound)]</pre>
# Display the updated dataset without outliers
print("\nDataset without outliers:")
print(df_no_outliers.head())
     Identified outliers:
        | Patient ID | Age | Sex | Cholesterol | Blood Pressure | Heart Rate | Diabetes | Family History | Smoking | Obesity | Alcohol C
     | 1 | CZE1114 | 230.0 | Male |
                                        389.0
                                               165/93
                                                               98.0
                                                                            | 1 |
                                                                                                         | 1 | 1 |
    Dataset without outliers:
      Patient ID Age
                          Sex Cholesterol Blood Pressure Heart Rate Diabetes
     0
          kjreer
                  67.0
                          Male
                                     208.0
                                                   158/88
                                                                 72.0
         BNI9906 21.0
                                                   174/99
                                      324.0
                                                                 72.0
     2
                            Х
                                                                              1
                                     318.0
                                                    91/88
     4
         Z007941 66.0
                          Male
                                                                 93.0
                                                                              1
     5
         Z007941
                  54.0 Female
                                     297.0
                                                   172/86
                                                                 48.0
                                                                              1
         WYV0966 90.0
                                                   102/73
     6
                          Male
                                     358.0
                                                                 84.0
        Family History
                       Smoking Obesity ... Sedentary Hours Per Day Income
     0
                             1
                                      0 ...
                                                           6.615001 261404
                                      0 ...
     2
                    0
                             0
                                                            9.463426
                                                                      235282
     4
                    1
                             1
                                      1 ...
                                                            1.514821 160555
     5
                    1
                             1
                                                            7.798752 241339
                                        . . .
     6
                    0
                                      0
                                                            0.627356 190450
                             1
                                        . . .
             BMI Triglycerides Physical Activity Days Per Week \
     0
       31.251233
                            286
     2
        28.176571
                            587
                                                              4
       21.809144
     4
                            231
                                                              1
     5
        20.146839
                            795
                                                              5
       28.885811
                            284
        Sleep Hours Per Day
                              Country
                                          Continent
                                                              Hemisphere \
     0
                            Argentina South America Southern Hemisphere
                         6
     2
                         4
                               France
                                             Europe Northern Hemisphere
     4
                         5
                             Thailand
                                               Asia Northern Hemisphere
     5
                        10
                                              Europe Northern Hemisphere
                              Germany
     6
                        10
                               Canada North America Northern Hemisphere
        Heart Attack Risk
     0
                       0
     2
                       0
     4
                       a
     5
                       1
     6
                       1
     [5 rows x 26 columns]
```

import pandas as pd

[#] Load vour dataset

```
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# List of columns to check for missing values
columns_to_check = [
    'Patient ID', 'Age', 'Sex', 'Cholesterol', 'Blood Pressure', 'Heart Rate',
    'Diabetes', 'Family History', 'Smoking', 'Obesity', 'Alcohol Consumption', 'Exercise Hours Per Week', 'Diet', 'Previous Heart Problems', 'Medication Use',
    'Stress Level', 'Sedentary Hours Per Day', 'Income', 'BMI', 'Triglycerides',
    'Physical Activity Days Per Week', 'Sleep Hours Per Day', 'Country',
    'Continent', 'Hemisphere', 'Heart Attack Risk'
# Iterate over columns and check for missing values
missing_values_info = []
for column in columns_to_check:
    num_missing_values = df[column].isnull().sum()
    missing_values_info.append({'Column': column, 'Missing Values': num_missing_values})
# Create a DataFrame from the information
missing_values_df = pd.DataFrame(missing_values_info)
# Display the information about missing values
print(missing_values_df)
```

	C - 1	M' ' W-1
_	Column	
0	Patient ID	0
1	Age	2
2	Sex	3
3	Cholesterol	1
4	Blood Pressure	0
5	Heart Rate	1
6	Diabetes	0
7	Family History	0
8	Smoking	0
9	Obesity	0
10	Alcohol Consumption	0
11	Exercise Hours Per Week	0
12	Diet	0
13	Previous Heart Problems	0
14	Medication Use	0
15	Stress Level	0
16	Sedentary Hours Per Day	0
17	Income	0
18	BMI	0
19	Triglycerides	0
20	Physical Activity Days Per Week	0
21	Sleep Hours Per Day	0
22	Country	0
23	Continent	0
24	Hemisphere	0
25	Heart Attack Risk	0
23	meal C ACCACK NISK	0

```
import pandas as pd
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# List of columns to check for missing values
columns_to_check = [
    'Patient ID', 'Age', 'Sex', 'Cholesterol', 'Blood Pressure', 'Heart Rate',
    'Diabetes', 'Family History', 'Smoking', 'Obesity', 'Alcohol Consumption', 'Exercise Hours Per Week', 'Diet', 'Previous Heart Problems', 'Medication Use',
    'Stress Level', 'Sedentary Hours Per Day', 'Income', 'BMI', 'Triglycerides',
    'Physical Activity Days Per Week', 'Sleep Hours Per Day', 'Country',
    'Continent', 'Hemisphere', 'Heart Attack Risk'
]
# Iterate over columns and check for missing values
missing_values_info = []
for column in columns_to_check:
    missing_rows = df[df[column].isnull()]
    if not missing_rows.empty:
        missing_values_info.append({'Column': column, 'Missing Rows': missing_rows})
        missing_values_info.append({'Column': column, 'Missing Rows': None})
# Display the information about missing values
for info in missing_values_info:
    print(f"\nColumn '{info['Column']}':")
    if info['Missing Rows'] is not None:
        print(f"Missing values located at:\n{info['Missing Rows']}")
    else:
        print("No missing values.")
```

```
Column 'Country':
No missing values.

Column 'Continent':
No missing values.

Column 'Hemisphere':
No missing values.

Column 'Heart Attack Risk':
No missing values.
```

checking the single schema problem

single shema problems

```
def validate_bmi(bmi):
      return 0 <= bmi if pd.notna(bmi) else None
def accurate_bmi(bmi):
     return 9 <= bmi <= 105 if pd.notna(bmi) else None
column_name = "BMI"
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_bmi).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df[column_name].apply(accurate_bmi)
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table_data list
table_data.append([column_name, num_data, num_null, f"{validity:.2f}%", f"{accuracy_percentage:.2f}%",f"{completeness:.2f}%","-","-"])
# Create a DataFrame from the table_data list
result table = pd.DataFrame(table data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
def validate_age(age):
      return 0 <= age <= 150 if pd.notna(age) else None
# Attribute: 'Age'
column_name = 'Age
# Number of Data
num_data = df[column_name].count()
# Null
num_null = df[column_name].isnull().sum()
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Validity based on the specified pattern
validity = (df[column_name].apply(validate_age).sum() / num_data) * 100 if num_data > 0 else None
# Accuracy
accuracy_series = df['Age'].apply(lambda x: 0 <= x <= 150 if pd.notna(x) else None)
accuracy = accuracy series.all()
# Accuracy Percentage
accuracy_percentage = (accuracy_series.sum() / num_data) * 100 if num_data > 0 else None
# Append the results to the table data list
table\_data.append([column\_name, num\_data, num\_null, f"\{validity:.2f\}\%", f"\{accuracy\_percentage:.2f\}\%", f"\{completeness:.2f\}\%", f"[validity:.2f\}\%", f"[accuracy\_percentage:.2f]\%", f"[completeness:.2f]\%", f"[validity:.2f]\%", f"[accuracy\_percentage:.2f]\%", f"[completeness:.2f]\%", f"[completeness
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Print rows where 'Age' does not match the criteria
# invalid_age_rows = df[~df['Age'].apply(validate_age)]
# print("\nRows where 'Age' does not match the criteria:")
# print(tabulate(invalid_age_rows, headers='keys', tablefmt='pretty'))
def validate_patient_id(patient_id):
      pattern = re.compile(r'^[A-Za-z]{3}\d{4}$')
      return bool(pattern.match(str(patient id)))
# Check the uniqueness of 'Patient ID'
is_unique = df['Patient ID'].nunique() / len(df)
# Find non-unique 'Patient IDs'
non_unique_patient_ids = df[df.duplicated(subset='Patient ID', keep=False)]['Patient ID']
# Attribute: 'Patient ID'
column_name = 'Patient ID'
# Number of Data
num_data = len(df)
# Null
num_null = df[column_name].isnull().sum()
# Validity based on the specified pattern
# Completeness
completeness = (1 - (num_null / num_data)) * 100
# Consistency (Uniqueness)
consistency = is_unique * 100
# Append the results to the table_data list
table\_data.append([column\_name, num\_data, num\_null, f"\{validity:.2f\}\%", "-", f"\{completeness:.2f\}\%", f"\{consistency:.2f\}\%", "-"])
# Create a DataFrame from the table_data list
result_table = pd.DataFrame(table_data, columns=["Name of the Attribute", "Number of Data", "Null", "Validity", "Accuracy", "Completeness",
# Display the result table using tabulate for a nice format
```

```
#print(tabulate(result table, headers='keys', tablefmt='pretty'))
# Print non-unique 'Patient IDs'
print("\nNon-unique Patient IDs:")
print(non_unique_patient_ids)
     Non-unique Patient IDs:
            Z007941
            Z007941
     5
     539
            DF07465
     540
            DF07465
     Name: Patient ID, dtype: object
import pandas as pd
from tabulate import tabulate
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# List of columns to check for missing values, uniqueness, and validation
columns to check = [
    'Patient ID', 'Age', 'Sex', 'Cholesterol', 'Blood Pressure', 'Heart Rate',
    'Diabetes', 'Family History', 'Smoking', 'Obesity', 'Alcohol Consumption',
    'Exercise Hours Per Week', 'Diet', 'Previous Heart Problems', 'Medication Use',
    'Stress Level', 'Sedentary Hours Per Day', 'Income', 'BMI', 'Triglycerides',
    'Physical Activity Days Per Week', 'Sleep Hours Per Day', 'Country',
    'Continent', 'Hemisphere', 'Heart Attack Risk'
# Create a list to store the information for each column
column_info = []
# Iterate over columns and check for missing values, uniqueness, and validation
for column in columns to check:
    missing_rows = df[df[column].isnull()]
    duplicate_rows = df[df.duplicated(subset=[column], keep=False)]
    # Validation checks for specific columns
    validation_check = None
    if column == 'Age':
        validation_check = df['Age'].apply(lambda x: 0 <= x if pd.notna(x) else None)</pre>
    elif column == 'BMI':
        validation_check = df['BMI'].apply(lambda x: 0 <= x if pd.notna(x) else None)
    info = {
        'Column': column,
        'Missing Rows': missing_rows.head(),
        'Duplicate Rows': duplicate_rows.head(),
        'Validation Check': validation_check
    column_info.append(info)
# Display the information about missing values, uniqueness, and validation in a table
for info in column info:
    print(f"\nColumn '{info['Column']}':")
    # Format missing values
    missing_values_table = tabulate(info['Missing Rows'], headers='keys', tablefmt='pretty')
    print(f"Missing values located at:\n{missing_values_table if info['Missing Rows'].shape[0] else 'No missing values.'}")
    # Format duplicate values
    # duplicate_values_table = tabulate(info['Duplicate Rows'], headers='keys', tablefmt='pretty')
    # print(f"Duplicated values located at:\n{duplicate_values_table if info['Duplicate Rows'].shape[0] else 'No duplicated values.'}")
    # Format validation check
    if info['Validation Check'] is not None:
        invalid rows = df[~info['Validation Check'].fillna(False)]
        if not invalid_rows.empty:
            invalid_rows_table = tabulate(invalid_rows, headers='keys', tablefmt='pretty')
            print(f"Invalid rows based on validation check:\n{invalid_rows_table}")
        else:
            print("All rows are valid.")
    else:
        print("No validation check performed for this column.")
```

```
No missing values.
No validation check performed for this column.
Column 'Stress Level':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Sedentary Hours Per Day':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Income':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'BMI':
Missing values located at:
No missing values.
All rows are valid.
Column 'Triglycerides':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Physical Activity Days Per Week':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Sleep Hours Per Day':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Country':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Continent':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Hemisphere':
Missing values located at:
No missing values.
No validation check performed for this column.
Column 'Heart Attack Risk':
Missing values located at:
No missing values.
No validation check performed for this column.
```

instant level single source

```
import pandas as pd

# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)

# Check for duplicated rows
duplicated_rows = df[df.duplicated()]

# Check for duplicated columns
duplicated_columns = df.columns[df.columns.duplicated()]

# Calculate the correlation matrix
correlation_matrix = df.corr()

# Display the results
print("Duplicated Rows:")
print(duplicated_rows)
```

print("\nDuplicated Columns:")
print(duplicated_columns)

```
print("\nCorrelation Matrix:")
print(correlation_matrix)
    Obesity
                                     -0.003870 -0.006058
                                                               0.001467
    Alcohol Consumption
                                     -0.022396 0.010562
                                                               0.006169
    Exercise Hours Per Week
                                     -0.023414
                                                0.003777
                                                               0.001717
    Previous Heart Problems
                                     -0.003281
                                                0.015718
                                                              -0.019029
    Medication Use
                                     -0.003464 0.009514
                                                              -0.011095
    Stress Level
                                     -0.002760 -0.003250
                                                              -0.003921
                                      0.003511 -0.000024
                                                              -0.005785
    Sedentary Hours Per Day
    Income
                                      1.000000 0.008836
                                                               0.010739
                                      0.008836 1.000000
    BMI
                                                              -0.005964
    Triglycerides
                                      0.010739 -0.005964
                                                               1.000000
    Physical Activity Days Per Week 0.000130 0.008110
                                                              -0.007556
    Sleep Hours Per Day
                                     -0.006598 -0.010030
                                                              -0.029216
    Heart Attack Risk
                                      0.009628 0.000020
                                                               0.010471
                                      Physical Activity Days Per Week \
    Age
                                                             0.000376
    Cholesterol
                                                             0.015874
    Heart Rate
                                                             0.000820
    Diabetes
                                                            -0.002411
    Family History
                                                             0.009561
                                                            -0.006465
    Smoking
    Obesity
                                                             0.005337
    Alcohol Consumption
                                                             0.001593
    Exercise Hours Per Week
                                                             0.007725
    Previous Heart Problems
                                                             0.008537
    Medication Use
                                                            -0.011139
    Stress Level
                                                             0.007405
    Sedentary Hours Per Day
                                                            -0.006178
    Income
                                                             0.000130
    BMI
                                                             0.008110
    Triglycerides
                                                            -0.007556
    Physical Activity Days Per Week
                                                             1.000000
    Sleep Hours Per Day
                                                             0.014033
    Heart Attack Risk
                                                            -0.005014
                                      Sleep Hours Per Day Heart Attack Risk
                                                                    0.005791
                                                -0.001774
    Age
    Cholesterol
                                                 0.004540
                                                                    0.019571
    Heart Rate
                                                 0.001745
                                                                   -0.004202
    Diabetes
                                                -0.012457
                                                                    0.017225
    Family History
                                                -0.011199
                                                                   -0.001652
                                                                   -0.004051
    Smoking
                                                -0.005424
    Obesity
                                                -0.005314
                                                                   -0.013318
    Alcohol Consumption
                                                -0.000843
                                                                   -0.013778
    Exercise Hours Per Week
                                                -0.001245
                                                                    0.011133
    Previous Heart Problems
                                                 0.004460
                                                                    0.000274
    Medication Use
                                                -0.020393
                                                                    0.002234
                                                -0.014205
                                                                   -0.004111
    Stress Level
    Sedentary Hours Per Day
                                                 0.004792
                                                                   -0.005613
    Income
                                                -0.006598
                                                                    0.009628
    BMI
                                                -0.010030
                                                                    0.000020
    Triglycerides
                                                -0.029216
                                                                    0.010471
    Physical Activity Days Per Week
                                                 0.014033
                                                                   -0.005014
    Sleep Hours Per Day
                                                 1.000000
                                                                    -0.018528
    Heart Attack Risk
                                                                    1.000000
                                                -0.018528
    <ipython-input-15-6ba120e0b2a0>:15: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ver
      correlation_matrix = df.corr()
```

single source instant level

Multisource instant level:

Continent

Contradictory Data that have the same Country name but different

the same country have two different name like "US" and "United States"

Country (main csv) is not in nation (continent csv)

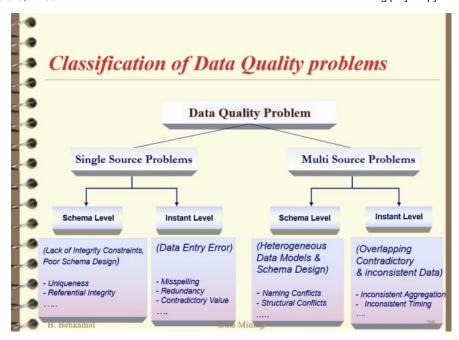
```
import pandas as pd
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# Check for duplicated rows
duplicated_rows = df[df.duplicated()]
# Check for duplicated columns
duplicated_columns = df.columns[df.columns.duplicated()]
# Calculate the correlation matrix
# correlation_matrix = df.corr()
# Display the redundant values
print("Duplicated Rows:")
print(duplicated_rows)
print("\nDuplicated Columns:")
print(duplicated_columns)
# print("\nCorrelation Matrix:")
# print(correlation_matrix)
     Duplicated Rows:
     Empty DataFrame
     Columns: [Patient ID, Age, Sex, Cholesterol, Blood Pressure, Heart Rate, Diabetes, Family History, Smoking, Obesity, Alcohol Consumptio
     Index: []
     [0 rows x 26 columns]
     Duplicated Columns:
     Index([], dtype='object')
                                                           (3)
                                                                ....
                                                                        Single Schema: uniquness -> Patient Id should be unique Missing value ->
Single Schema:
           uniquness -> Patient Id should be unique
           Missing value -> some columns should be not null
                                                                        be between 0 until 180
           invalid value -> for example age should be between 0 until
           180
                                                                        Hemisphere BMI > 105 is misspell
single instant level :
Misspelling value for continent
                                                                        Multi source Schema level: Naming conflict between main dataset and
Misspelling value for Hemisphere
BMI > 105 is misspell
Multi source Schema level:
           Naming conflict between main dataset and continent dataset
                                                                        structure conflict between Male and Female and 0 and 1
           in Country column that we have in main dataset and nation i
           continent dataset and between Continent column and continen
           naming conflict between Gender in names.csv and Sex in main
           structure conflict between Male and Female and 0 and 1
                                                                        States"
```

some columns should be not null invalid value -> for example age should

single instant level: Misspelling value for continent Misspelling value for

continent dataset in Country column that we have in main dataset and nation in continent dataset and between Continent column and continent column naming conflict between Gender in names.csv and Sex in main csv

Multisource instant level: Contradictory Data that have the same Country name but different Continent Country (main csv) is not in nation (continent csv) the same country have two different name like "US" and "United



single instant level: Misspelling value for continent Misspelling value for Hemisphere BMI > 105 is misspell

Multi source Schema level: Naming conflict between main dataset and continent dataset in Country column that we have in main dataset and nation in continent dataset and between Continent column and continent column

```
for index, row in df.iterrows():
   Continent = row['Continent']
   Country = row['Country']
   Hemisphere = row['Hemisphere']
   if Country == "United States" :
       # Multi source Schema level: Naming conflict
       Country = "US"
    if not (Hemisphere == "Southern Hemisphere" or Hemisphere == "Northern Hemisphere"):
       # Misspelling value for Hemisphere
       print(f"Misspelling value for Hemisphere with index {index}")
    if not (Continent == "South America" or Continent == "North America" or Continent == "Europe" or Continent == "Asia" or Continent == "A
        # Misspelling value for Continent
       print(f"Misspelling value for Hemisphere with index {index}")
   result = continentcsv[continentcsv['nation'] == Country]['continent'].values
    if len(result) > 0:
       if result != Continent:
            if result[0] == 'Oceania' and Continent=='Australia':
                # Multi source Schema level: Naming conflict
                continue
            # Contradictory Data that have the same Country name but different Continent
            print(f"The continent for {Country} is: {result[0]} but in main csv writed as: {Continent}")
    else:
       # Country (main csv) is not in nation (continent csv)
       print(f"The Country {Country} does not exist in the continentcsv.")
     Misspelling value for Hemisphere with index 10
     The continent for South Africa is: Africa but in main csv writed as: a
     The Country B does not exist in the continentcsv.
```

```
for index, row in df.iterrows():
    Sex = row['Sex']
    patient = row['Patient ID']
    if Sex == "Male":
        Sex = "0"
    if Sex == "Female":
        Sex = "1"
    result = names[names['Patient ID'] == patient]['Gender'].values
    if len(result) > 0:
        if result[0] != Sex:
            print(f"The dataset names for sex is: {result[0]} but in the main csv written as: {Sex}")
    else:
        \label{print} \mbox{print(f"The patient ID {patient}) does not exist in the names.csv")}
     The dataset names for sex is: 0 but in the main csv written as: 1 \,
     The dataset names for sex is: nan but in the main csv written as: nan
     The dataset names for sex is: nan but in the main csv written as: nan
     The dataset names for sex is: nan but in the main csv written as: nan
     The patient ID OFE0541 does not exist in the names.csv
     The patient ID YFE0882 does not exist in the names.csv
```

```
import pandas as pd
from tabulate import tabulate
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# List of columns to check for missing values, uniqueness, and validation
columns_to_check = [
     'Age', 'BMI'
1
# Create a list to store the information for each column
column_info = []
# Iterate over columns and check for missing values, uniqueness, and validation
for column in columns_to_check:
    missing_rows = df[df[column].isnull()]
    duplicate_rows = df[df.duplicated(subset=[column], keep=False)]
    # accuracy checks for specific columns
    accuarcy_check = None
    if column == 'Age':
       accuarcy_check = df['Age'].apply(lambda x: 0 <= x <150 if pd.notna(x) else None)
    elif column == 'BMI':
       accuarcy\_check = df['BMI'].apply(lambda x: 9 <= x < 105 if pd.notna(x) else None)
    info = {
        'Column': column,
        'Missing Rows': missing_rows.head(),
        'Duplicate Rows': duplicate_rows.head(),
        'accuracy Check': accuarcy_check
    }
    column_info.append(info)
# Display the information about missing values, uniqueness, and validation in a table
for info in column_info:
    print(f"\nColumn '{info['Column']}':")
    # Format missing values
    # missing_values_table = tabulate(info['Missing Rows'], headers='keys', tablefmt='pretty')
    # print(f"Missing values located at:\n{missing_values_table if info['Missing Rows'].shape[0] else 'No missing values.'}")
    # Format duplicate values
    # duplicate_values_table = tabulate(info['Duplicate Rows'], headers='keys', tablefmt='pretty')
    # print(f"Duplicated values located at:\n{duplicate_values_table if info['Duplicate Rows'].shape[0] else 'No duplicated values.'}")
    # Format unaccurate check
    if info['accuracy Check'] is not None:
       unaccurate_rows = df[~info['accuracy Check'].fillna(False)]
        if not unaccurate_rows.empty:
           unaccurate_rows_table = tabulate(unaccurate_rows, headers='keys', tablefmt='pretty')
           print(f"unaccurate rows based on accuracy check:\n{unaccurate_rows_table}")
        else:
            print("All rows are vaccurate.")
       print("No accuracy check performed for this column.")
     Column 'Age':
     unaccurate rows based on accuracy check:
          | Patient ID | Age | Sex | Cholesterol | Blood Pressure | Heart Rate | Diabetes | Family History | Smoking | Obesity | Alcoh
     | 1 | CZE1114
                       | 230.0 | Male |
                                             389.0
                                                            165/93
                                                                            98.0
     3 | JLN3497
                       | nan | Male |
                                             383.0
                                                           163/100
                                                                            73.0
                                                                                         1
                                                                                                                               0
                                                                                                       1
                                                                                                                     1
     | 602 | RON2853 | nan | Female |
                                             224.0
                                                            136/71
                                                                            97.0
                                                                                         a
                                                                                                       1
                                                                                                                     1
                                                                                                                               a
     Column 'BMI':
     All rows are vaccurate.
```

Double-click (or enter) to edit

```
import pandas as pd
# Load your dataset
\# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# Check the number of unique values in each column
unique_value_counts = df.nunique()
# Filter columns with non-unique values
non_unique_columns = unique_value_counts[unique_value_counts < len(df)].index</pre>
# Display the columns with non-unique values
print("Columns with Non-Unique Values:")
print(non_unique_columns)
     Columns with Non-Unique Values:
     'Alcohol Consumption', 'Diet', 'Previous Heart Problems',
             'Medication Use', 'Stress Level', 'Income', 'Triglycerides',
'Physical Activity Days Per Week', 'Sleep Hours Per Day', 'Country',
             'Continent', 'Hemisphere', 'Heart Attack Risk'],
            dtype='object')
برای بهبود کیفیت داده ستون قاره چون از کشور قابل استخراج است اضافه است. و همچنین ستون نیم کره اضافه است پس حذف میکنیم
به جای اینکه به صورت باینری خروجی را چاپ کنیم به صورت درصدی عدد را ثبت کنیم با این کار دقت مدل بالا میرود heart rist attackرای
اگر تعدا سطر های دارای مقادیر خالی برای یک ستون خاص کم بود باید با مقادیر نزدیک به اون جایگزتری کنیم
مقادیر تکرار شده رو یک بار استفاده کنیم
داده ها ختما یک مدل باشند
دیتا معتبر و درست باشند سطر های دارای مقادیر اشتباه را حذف میکنیم
```

replacing the missing values(null) with mean or median

```
import pandas as pd
from sklearn.impute import SimpleImputer
# Load your dataset
# Replace '/path/to/your/dataset.csv' with the actual path to your dataset
dataset_path = '/content/heart_attack_prediction_dataset.csv'
df = pd.read_csv(dataset_path)
# Set the threshold for dropping columns with more than X null values
null_threshold = 100
# Identify columns with more than the threshold null values
columns_to_drop = df.columns[df.isnull().sum() > null_threshold]
# Drop columns with more than the threshold null values
df.drop(columns=columns_to_drop, inplace=True)
# Create a DataFrame to store information about the replaced values
replaced_values_info = pd.DataFrame(columns=['Column', 'Replaced Nulls', 'Replacement Value', 'Reason'])
# Iterate over columns and fill missing values with mean, mode, or median
for column in df.columns:
    if df[column].isnull().any():
        # Determine fill value based on data type
        fill_value = df[column].mean() if pd.api.types.is_numeric_dtype(df[column].dtype) else df[column].mode().iloc[0]
        # Fill missing values
        replaced_rows = df[df[column].isnull()]
        df[column].fillna(fill_value, inplace=True)
        # Store information about replaced values
        replaced_values_info = replaced_values_info.append({
            'Column': column,
            'Replaced Nulls': len(replaced_rows),
            'Replacement Value': fill_value,
            'Reason': 'Mean' if pd.api.types.is_numeric_dtype(df[column].dtype) else 'Mode'
        }, ignore_index=True)
# Display the updated dataset
print(df)
# Display information about replaced values
print("\nInformation about replaced values:")
print(replaced_values_info)
          Patient ID
                                     Sex Cholesterol Blood Pressure Heart Rate \
                             Age
     0
              kjreer
                       67.000000
                                    Male
                                                 208.0
                                                               158/88
                                                                             72.0
     1
             CZE1114 230.000000
                                    Male
                                                 389.0
                                                               165/93
                                                                             98.0
             BNI9906
                       21,000000
                                                 324.0
                                                               174/99
     2
                                                                             72.0
                       53.724803
                                    Male
     3
             JLN3497
                                                 383.0
                                                              163/100
                                                                             73.0
     4
             Z007941
                       66.000000
                                                318.0
                                                                             93.0
                                    Male
                                                                91/88
                       60.000000
                                                121.0
             MSV9918
                                                                94/76
     8758
                                    Male
                                                                             61.0
     8759
             QSV6764
                       28.000000 Female
                                                 120.0
                                                              157/102
                                                                             73.0
     8760
             XKA5925
                       47.000000
                                    Male
                                                 250.0
                                                               161/75
                                                                            105.0
                       36.000000
             EPE6801
                                    Male
                                                178.0
                                                               119/67
     8761
                                                                             60.0
     8762
             ZWN9666
                       25.000000 Female
                                                356.0
                                                               138/67
                                                                             75.0
           Diabetes
                    Family History
                                     Smoking Obesity
                                                       ... \
     0
                  0
                                  0
                                            1
                                                     0
                                                        ...
     1
                  1
                                  1
                                            1
                                                     1
                                                       ...
     2
                  1
                                  0
                                            0
                                                     0
                                                        . . .
     3
                  1
                                  1
                                            1
                                                     0
                                                        ...
     4
                  1
                                  1
                                            1
                                                    1
                                                        . . .
                                                        . . .
     8758
                                  1
                                           1
                                                       . . .
     8759
                  1
                                  a
                                           a
                                                    1 ...
     8760
                  0
                                  1
                                            1
                                                     1
                                                        . . .
     8761
                  1
                                                       . . .
     8762
                  1
                                            0
                                                     0
                                                        . . .
           Sedentary Hours Per Day Income
                                                   BMI Triglycerides \
     0
                                    261404
                                            31,251233
                          6.615001
     1
                          4.963459
                                    285768
                                             27,194973
                                                                  235
     2
                          9.463426 235282
                                            28.176571
                                                                  587
     3
                          7.648981
                                    125640
                                             36.464704
                                                                  378
                                             21,809144
     4
                          1.514821
                                    160555
                                                                  231
                         10.806373 235420 19.655895
```

208.0

Sex Cholesterol Blood Pressure Heart Rate ∖

158/88

72.0

Patient ID

kjreer

Age

Male

67,000000