import pandas as pd heart = pd.read csv('heartdisease.csv') heart HeartDisease BMI Smoking AlcoholDrinking Stroke PhysicalHealth No 16.60 Yes No No 3.0 No 20.34 No No 1 Yes 0.0 2 No 26.58 Yes No No 20.0 3 No 24.21 No No No 0.0 No 23.71 No No No 28.0 . . . 319790 Yes 27.41 Yes No No 7.0 319791 No 29.84 No Yes No 0.0 319792 No 24.24 No No No 0.0 319793 No 32.81 No No No 0.0 No 46.56 319794 No No No 0.0 MentalHealth DiffWalking Sex AgeCategory Race Diabetic \ 30.0 Female 55-59 White No 0 Yes 0.0 Female 80 or older White 1 No No 30.0 Male 65-69 White 2 No Yes 3 0.0 No Female 75-79 White No 0.0 Female 40-44 4 Yes White No 319790 0.0 Yes Male 60-64 Hispanic Yes 319791 0.0 Male 35-39 Hispanic No No 319792 0.0 No Female 45-49 Hispanic

No		0.0		NI -	F 1 .		25 20	112 2 -	
319793		0.0		No	Female		25-29	Hispanic	
No		0 0		No	[omala	00 0	r aldar	Hienonie	
319794 No		0.0		No	remate	80 0	r older	Hispanic	
NO									
	PhysicalAc	tivitv	GenHe	alth	Sleer	Time	Δsthma K	CidneyDisease	
SkinCar		CIVICY	ocinic	Jacci	. 5000	71 11110 7	AS CIIIIIG IV	tuney Discuse	
0		Yes	Very	aood	d	5.0	Yes	No	
Yes			,	J					
1		Yes	Very	good	ł	7.0	No	No	
No									
2		Yes		Fair	-	8.0	Yes	No	
No									
3		No		Good	d	6.0	No	No	
Yes		.,							
4		Yes	Very	good	1	8.0	No	No	
No									
				• • •					
319790		No		Fair	•	6.0	Yes	No	
No		NO		таті		0.0	163	INU	
319791		Yes	Very	anna	1	5.0	Yes	No	
No		105	1 C. J	9000	•	3.0	105	110	
319792		Yes		Good	d	6.0	No	No	
No									
319793		No		Good	ł	12.0	No	No	
No									
319794		Yes		Good	ł	8.0	No	No	
No									
[319795	5 rows x 18	columns	5]						
#micica	20 127								
#misisr	ng values								
near t.									

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 319795 entries, 0 to 319794
Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
0	HeartDisease	319795 non-null	object
1	BMI	319795 non-null	float64
2	Smoking	319795 non-null	object
3	AlcoholDrinking	319795 non-null	object
4	Stroke	319795 non-null	object
5	PhysicalHealth	319795 non-null	float64
6	MentalHealth	319795 non-null	float64
7	DiffWalking	319795 non-null	object
8	Sex	319795 non-null	object
			-

```
9
                       319795 non-null
    AgeCategory
                                        object
 10 Race
                       319795 non-null object
 11 Diabetic
                       319795 non-null object
 12 PhysicalActivity 319795 non-null
                                        object
 13 GenHealth
                       319795 non-null object
14 SleepTime
                       319795 non-null float64
15 Asthma
                       319795 non-null object
16 KidneyDisease
                       319795 non-null object
                       319795 non-null object
17 SkinCancer
dtypes: float64(4), object(14)
memory usage: 43.9+ MB
# Check for missing values
print(heart.isna().sum())
HeartDisease
                    0
                    0
BMI
                    0
Smoking
                    0
AlcoholDrinking
Stroke
                    0
PhysicalHealth
                    0
MentalHealth
                    0
DiffWalking
                    0
                    0
Sex
                    0
AgeCategory
                    0
Race
                    0
Diabetic
PhysicalActivity
                    0
GenHealth
                    0
SleepTime
                    0
                    0
Asthma
KidnevDisease
                    0
SkinCancer
                    0
dtype: int64
#Handling datatypes
from sklearn.preprocessing import LabelEncoder
# Initialize the LabelEncoder
label encoder = LabelEncoder()
# Identify columns with dtype 'object' to apply label encoding
categorical columns = heart.select dtypes(include=['object']).columns
# Apply label encoding to each categorical column
for col in categorical_columns:
   heart[col] = label encoder.fit transform(heart[col])
```

Display the first few rows of the encoded dataset print(heart.head())

HeartDiseas	se	BMI	Smoking	AlcoholDrinking	Stroke
PhysicalHealth	1	\			
0	0	16.60	1	0	Θ
3.0					
1	0	20.34	0	0	1
0.0					
2	0	26.58	1	0	0
20.0					
3	0	24.21	0	0	0
0.0					
4	0	23.71	0	0	0
28.0					

	MentalHealth	DiffWalking	Sex	AgeCategory	Race	Diabetic	\
0	30.0	0	0	7	5	2	
1	0.0	0	0	12	5	0	
2	30.0	0	1	9	5	2	
3	0.0	0	0	11	5	0	
4	0.0	1	0	4	5	0	

PhysicalActivit	:y	GenHealth	SleepTime	Asthma	KidneyDisease
SkinCancer					
0	1	4	5.0	1	Θ
1					
1	1	4	7.0	0	0
Θ					
2	1	1	8.0	1	0
Θ					
3	0	2	6.0	Θ	0
1					
4	1	4	8.0	0	0
0					

print(heart.dtypes)

HeartDisease	int32
BMI	float64
Smoking	int32
AlcoholDrinking	int32
Stroke	int32
PhysicalHealth	float64
MentalHealth	float64
DiffWalking	int32
Sex	int32
AgeCategory	int32
Race	int32
Diabetic	int32

```
PhysicalActivity
                      int32
GenHealth
                      int32
SleepTime
                    float64
Asthma
                      int32
KidneyDisease
                      int32
SkinCancer
                      int32
dtype: object
#Identifying outliers
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = heart['BMI'].quantile(0.25)
Q3 = heart['BMI'].quantile(0.75)
# Calculate IOR
IQR = 03 - 01
# Define the lower and upper bounds for outliers
lower bound = Q1 - 1.5 * IQR
upper bound = Q3 + 1.5 * IQR
# Identify outliers
outliers = heart[(heart['BMI'] < lower_bound) | (heart['BMI'] >
upper_bound)]
print("Outliers based on IQR method:\n", outliers)
Outliers based on IQR method:
                         BMI Smoking AlcoholDrinking Stroke
         HeartDisease
PhysicalHealth \
                      45.35
                                    0
                                                     0
                                                             0
32
30.0
57
                     46.52
                                    1
                                                     0
                                                             0
30.0
90
                   0
                     44.29
                                    0
                                                             0
30.0
105
                      58.54
                                    0
30.0
                                    0
107
                     45.42
                                                     0
                                                             0
0.0
. . .
319693
                     44.29
0.0
319709
                      51.46
                                    1
                                                             0
30.0
319725
                     53.16
                                    0
                                                             0
29.0
                   0 42.57
319777
                                                             0
0.0
319794
                   0 46.56
                                    0
                                                     0
                                                             0
0.0
```

32 57 90 105 107 319693 319709 319725 319777	MentalHealth 0.0 0.0 10.0 0.0 0.0 0.0 0.0 0.0 0.0	Dif	fWalking 1 0 1 0 0 0 1 1	Sex	AgeCate	gory 10 9 10 9 5 1 7 1 8	Race 5 5 4 5	Diabetic \ 2 2 0 1 0 0 0 1 0
319794	0.0		0	0		12	3	0
	PhysicalActiv	ity	GenHealt	h Sl	eepTime	Asthm	a Ki	dneyDisease
\ 32		0		2	8.0		0	0
57		0	:	3	8.0		1	0
90		0		1	7.0		0	Θ
105		1		3	3.0		1	Θ
107		1		4	7.0		1	Θ
				•				
319693		1		4	7.0		0	Θ
319709		1		2	7.0		1	0
319725		0		1	5.0		1	0
319777		0		2	7.0		0	0
319794		1		2	8.0		0	0
32 57 90 105 107 319693 319709 319725 319777 319794	SkinCancer 0 0 1 0 0 0 0 0 0 0 0 0							

```
[10396 rows x 18 columns]
#removing
# Remove outliers by filtering the data within the bounds
heart cleaned = heart[(heart['BMI'] >= lower bound) & (heart['BMI'] <=</pre>
upper bound)]
# Display the cleaned dataset
print("Data after removing outliers:\n", heart cleaned.head())
Data after removing outliers:
    HeartDisease BMI Smoking AlcoholDrinking Stroke
PhysicalHealth
              0 16.60
                               1
                                                 0
                                                         0
3.0
                 20.34
1
                               0
0.0
                 26.58
                               1
                                                         0
20.0
                 24.21
                                                         0
0.0
                 23.71
                               0
28.0
   MentalHealth
                 DiffWalking
                               Sex AgeCategory Race
                                                        Diabetic \
0
           30.0
                                                     5
                            0
                                 0
                                                               2
                                                     5
1
            0.0
                            0
                                 0
                                              12
                                                               0
2
                                 1
                                                     5
                                                               2
                            0
                                              9
           30.0
3
                                              11
                                                     5
                                                               0
            0.0
                            0
                                 0
            0.0
                            1
                                 0
                                               4
                                                     5
                                                               0
   PhysicalActivity GenHealth SleepTime Asthma
                                                     KidneyDisease
SkinCancer
                                       5.0
                                                                 0
0
                                                  1
1
1
                                       7.0
                                                                 0
                                                  0
0
2
                                       8.0
                                                                 0
                                                  1
0
3
                                       6.0
                                                  0
                                                                 0
1
4
                                       8.0
                                                  0
                                                                 0
#Normalization
# Select all numerical columns including 'float64'
numerical_columns = heart.select_dtypes(include=['float64']).columns
# Apply Min-Max scaling or Standardization to all numerical columns
```

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
heart[numerical columns] =
scaler.fit transform(heart[numerical columns])
print(heart.dtypes)
HeartDisease
                      int32
                    float64
BMI
Smokina
                      int32
AlcoholDrinking
                      int32
Stroke
                      int32
PhysicalHealth
                    float64
MentalHealth
                    float64
DiffWalking
                      int32
Sex
                      int32
AgeCategory
                      int32
Race
                      int32
Diabetic
                      int32
PhysicalActivity
                      int32
GenHealth
                      int32
SleepTime
                    float64
Asthma
                      int32
                      int32
KidneyDisease
SkinCancer
                      int32
dtype: object
```

Apply decision tree

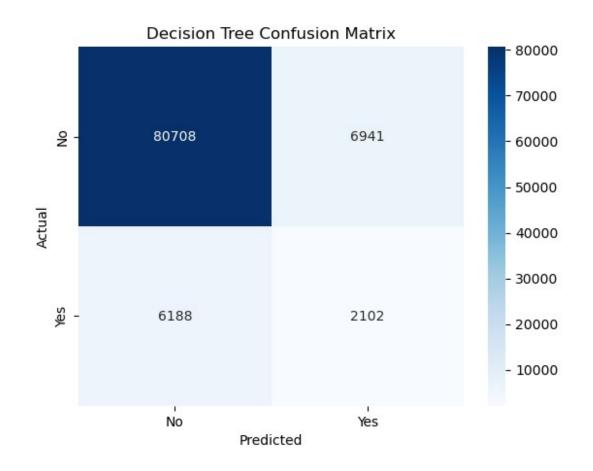
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, accuracy_score,
classification_report
import seaborn as sns
import matplotlib.pyplot as plt

# Split the dataset into features (X) and target (y)
X = heart.drop('HeartDisease', axis=1) # Features
y = heart['HeartDisease'] # Target variable

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Initialize the Decision Tree Classifier
dt_classifier = DecisionTreeClassifier(random_state=42)
```

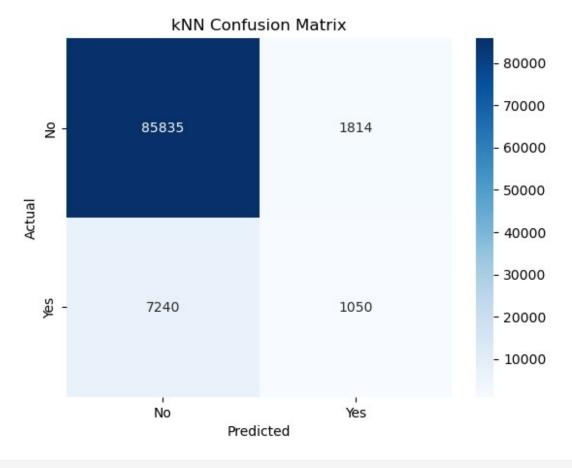
```
# Fit the model on the training data
dt classifier.fit(X train, y train)
# Make predictions
y pred dt = dt classifier.predict(X test)
# Evaluate the model
dt accuracy = accuracy score(y test, y pred dt)
dt conf matrix = confusion matrix(y test, y pred dt)
# Display results
print("Decision Tree Accuracy: ", dt accuracy)
print("Classification Report:\n", classification_report(y_test,
y pred dt))
# Plot Confusion Matrix (Heatmap)
sns.heatmap(dt conf matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.title('Decision Tree Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
Decision Tree Accuracy: 0.8631526282325227
Classification Report:
                            recall f1-score support
               precision
           0
                   0.93
                             0.92
                                       0.92
                                                87649
           1
                             0.25
                   0.23
                                       0.24
                                                 8290
    accuracy
                                       0.86
                                                95939
                   0.58
                             0.59
                                       0.58
                                                95939
   macro avg
weighted avg
                   0.87
                             0.86
                                       0.87
                                                95939
```



KNN

```
from sklearn.neighbors import KNeighborsClassifier
# Initialize the kNN classifier
knn_classifier = KNeighborsClassifier(n_neighbors=5)
# Fit the model on the training data
knn_classifier.fit(X_train, y_train)
# Make predictions
y_pred_knn = knn_classifier.predict(X_test)
# Evaluate the model
knn_accuracy = accuracy_score(y_test, y_pred_knn)
knn_conf_matrix = confusion_matrix(y_test, y_pred_knn)
# Display results
print("kNN Accuracy: ", knn_accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred_knn))
```

```
# Plot Confusion Matrix (Heatmap)
sns.heatmap(knn_conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.title('kNN Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
kNN Accuracy:
               0.9056275341623323
Classification Report:
               precision
                            recall f1-score support
           0
                   0.92
                             0.98
                                       0.95
                                                 87649
           1
                                       0.19
                   0.37
                             0.13
                                                 8290
                                       0.91
                                                 95939
    accuracy
                   0.64
                             0.55
                                       0.57
                                                 95939
   macro avg
weighted avg
                   0.87
                             0.91
                                       0.88
                                                 95939
```



#Conaprison ROC from sklearn.metrics import roc_curve, auc import matplotlib.pyplot as plt

```
# Compute ROC curve for Decision Tree
fpr_dt, tpr_dt, _ = roc_curve(y_test,
dt classifier.predict proba(X test)[:, 1])
roc auc_dt = auc(fpr_dt, tpr_dt)
# Compute ROC curve for kNN
fpr_knn, tpr_knn, _ = roc_curve(y_test,
knn classifier.predict proba(X test)[:, 1])
roc auc knn = auc(fpr knn, tpr knn)
# Plot ROC curves for both models
plt.figure(figsize=(10, 6))
plt.plot(fpr_dt, tpr_dt, color='blue', lw=2, label=f'Decision Tree
(AUC = \{roc \ auc \ dt:.\overline{2}f\})')
plt.plot(fpr knn, tpr knn, color='green', lw=2, label=f'kNN (AUC =
{roc auc knn:.2f})')
plt.\overline{plot([0, 1], [0, 1], color='gray', linestyle='--')} # Random
classifier line
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```

