MINOR PROJECT

import numpy as no

▼ TASK 1 - Exploratory Data Analysis

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv("/content/HepatitisCdata.csv")
df.head(5)

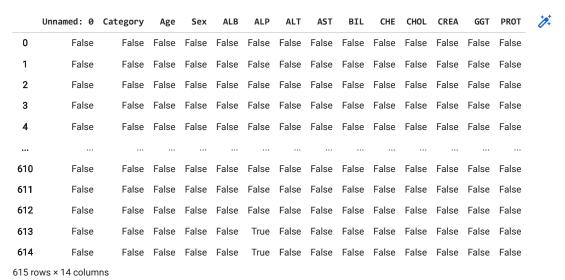
	Unnamed:	0	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	1
0		1	0=Blood Donor	32	m	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0	
1		2	0=Blood Donor	32	m	38.5	70.3	18.0	24.7	3.9	11.17	4.80	74.0	15.6	76.5	
2		3	0=Blood Donor	32	m	46.9	74.7	36.2	52.6	6.1	8.84	5.20	86.0	33.2	79.3	
3		4	0=Blood Donor	32	m	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7	
4		5	0=Blood Donor	32	m	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7	



QUESTION 1

- Are there any missing values in the dataset?
- If so, how will you handle them?
- What is the distribution of different diagnosis categories in the dataset?

#Are there any missing values in the dataset?
df.isnull()



df.isnull().sum()

Unnamed:	0	0
Category		0
Age		0
Sex		0
ALB		1
ALP		18
ALT		1

```
AST 0
BIL 0
CHE 0
CHOL 10
CREA 0
GGT 0
PROT 1
dtype: int64
```

therefore, from the above analysis we get the column names and their respective count of null values.

In order to handle these we can fill in the missing values as "NA"

```
df=df.fillna(value="NA")
```

df.isnull()

	Unnamed: 0	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
•••														
610	False	False	False	False	False	False	False	False	False	False	False	False	False	False
611	False	False	False	False	False	False	False	False	False	False	False	False	False	False
612	False	False	False	False	False	False	False	False	False	False	False	False	False	False
613	False	False	False	False	False	False	False	False	False	False	False	False	False	False
614	False	False	False	False	False	False	False	False	False	False	False	False	False	False

615 rows × 14 columns

```
df.isnull().sum()
```

Unnamed: 0 0 0 Category Age 0 Sex ALB 0 ALP ALT 0 0 0 AST BIL CHE CHOL 0 CREA GGT 0 PROT 0 dtype: int64

#What is the distribution of different diagnosis categories in the dataset?

```
data=df['Category'].value_counts()
data
```

0=Blood Donor 533
3=Cirrhosis 30
1=Hepatitis 24
2=Fibrosis 21
0s=suspect Blood Donor 7
Name: Category, dtype: int64

Summarizing your analysis and observation

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Perform feature encoding or transformation on categorical variables (such as sex) in the dataset. Which encoding technique would be most suitable?

df.head()

	Unnamed:	0	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0		1	0=Blood Donor	32	m	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0
1		2	0=Blood Donor	32	m	38.5	70.3	18.0	24.7	3.9	11.17	4.8	74.0	15.6	76.5
2		3	0=Blood Donor	32	m	46.9	74.7	36.2	52.6	6.1	8.84	5.2	86.0	33.2	79.3
3		4	0=Blood Donor	32	m	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7
4		5	0=Blood Donor	32	m	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7

encoded_data = pd.get_dummies(df, columns=["Sex"])
print(encoded_data.tail(10))

	Unnamed:	0 Ca	tegory	Age	ALB	ALP	ALT	AST	BIL	CHE	\
605	60	6 3=Cir	rhosis	42	33.0	79.0	3.7	55.7	200.0	1.72	
606	60	7 3=Cir	rhosis	49	33.0	190.7	1.2	36.3	7.0	6.92	
607	60	8 3=Cir	rhosis	52	39.0	37.0	1.3	30.4	21.0	6.33	
608	60	9 3=Cir	rhosis	58	34.0	46.4	15.0	150.0	8.0	6.26	
609	61	0 3=Cir	rhosis	59	39.0	51.3	19.6	285.8	40.0	5.77	
610	61	1 3=Cir	rhosis	62	32.0	416.6	5.9	110.3	50.0	5.57	
611	61	2 3=Cir	rhosis	64	24.0	102.8	2.9	44.4	20.0	1.54	
612	61	3 3=Cir	rhosis	64	29.0	87.3	3.5	99.0	48.0	1.66	
613	61	4 3=Cir	rhosis	46	33.0	NA	39.0	62.0	20.0	3.56	
614	61	5 3=Cir	rhosis	59	36.0	NA	100.0	80.0	12.0	9.07	
	CHOL CR	EA GO	T PROT	Sex	_f Se	x_m					

	CHOL	CREA	GGT	PROT	Sex_f	Sex_m
605	5.16	89.1	146.3	69.9	1	0
606	3.82	485.9	112.0	58.5	1	0
607	3.78	158.2	142.5	82.7	1	0
608	3.98	56.0	49.7	80.6	1	0
609	4.51	136.1	101.1	70.5	1	0
610	6.3	55.7	650.9	68.5	1	0
611	3.02	63.0	35.9	71.3	1	0
612	3.63	66.7	64.2	82.0	1	0
613	4.2	52.0	50.0	71.0	1	0
614	5.3	67.0	34.0	68.0	1	0

Add more cells if required

Summarizing your analysis and observations

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Analyze the distribution and range of values for each clinical and demographic feature in the dataset. Are there any outliers or extreme values?

df.head()

	Unnamed:	0	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	Z
0		1	0=Blood Donor	32	m	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0	
1		2	0=Blood Donor	32	m	38.5	70.3	18.0	24.7	3.9	11.17	4.8	74.0	15.6	76.5	
2		3	0=Blood Donor	32	m	46.9	74.7	36.2	52.6	6.1	8.84	5.2	86.0	33.2	79.3	
3		4	0=Blood Donor	32	m	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7	
4		5	0=Blood Donor	32	m	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7	

Summarizing your analysis and observation

df.shape

(615, 14)

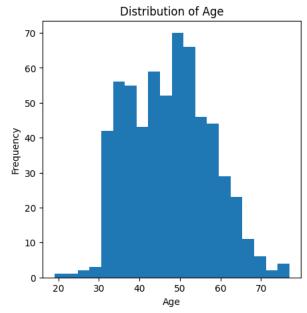
df.describe()

	Unnamed: 0	Age	AST	BIL	CHE	CREA	GGT	1
count	615.000000	615.000000	615.000000	615.000000	615.000000	615.000000	615.000000	
mean	308.000000	47.408130	34.786341	11.396748	8.196634	81.287805	39.533171	
std	177.679487	10.055105	33.090690	19.673150	2.205657	49.756166	54.661071	
min	1.000000	19.000000	10.600000	0.800000	1.420000	8.000000	4.500000	
25%	154.500000	39.000000	21.600000	5.300000	6.935000	67.000000	15.700000	
50%	308.000000	47.000000	25.900000	7.300000	8.260000	77.000000	23.300000	
75%	461.500000	54.000000	32.900000	11.200000	9.590000	88.000000	40.200000	
max	615.000000	77.000000	324.000000	254.000000	16.410000	1079.100000	650.900000	

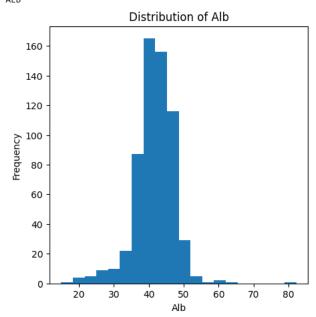
df.columns

```
dtype='object')
features=["Age","ALB","ALP","AST","BIL","CHE","CHOL","CREA","GGT","PROT"]
for feature in features:
 print(feature)
 plt.figure(figsize=(5,5))
 plt.hist(pd.to_numeric(df[feature], errors="coerce"), bins=20)
 plt.xlabel(feature.capitalize())
 plt.ylabel("Frequency")
 plt.title(f"Distribution of {feature.capitalize()}")
 plt.show()
 min=df[feature].min
 max=df[feature].max
 min_value = pd.to_numeric(df[feature], errors="coerce").min()
 max_value = pd.to_numeric(df[feature], errors="coerce").max()
 print(f"Range of values for {feature.capitalize()}: {min_value} - {max_value}")
```

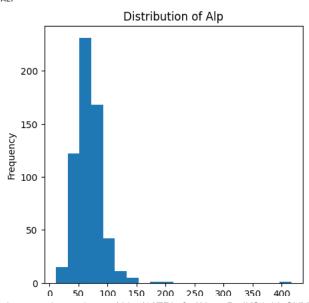




Range of values for Age: 19 - 77

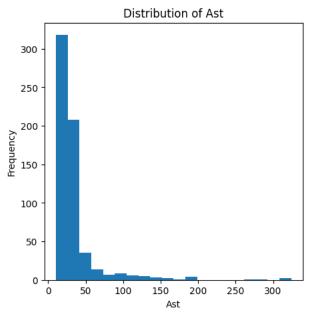


Range of values for Alb: 14.9 - 82.2 ALP

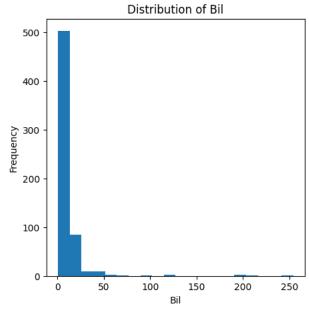


Alp

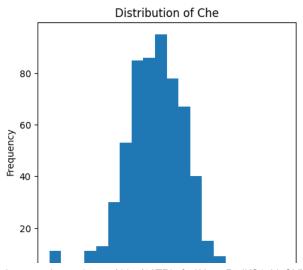
Range of values for Alp: 11.3 - 416.6

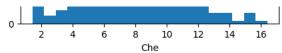


Range of values for Ast: 10.6 - 324.0

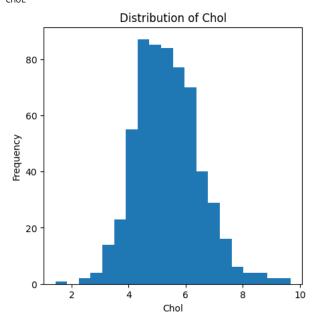


Range of values for Bil: 0.8 - 254.0 CHE

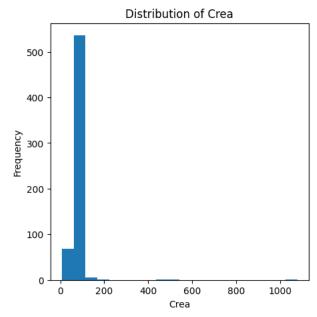




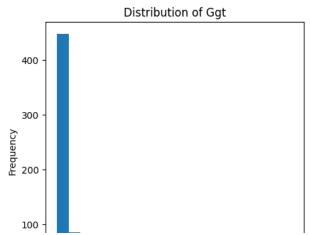
Range of values for Che: 1.42 - 16.41 $\ensuremath{\text{CHOL}}$

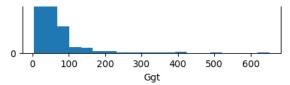


Range of values for Chol: 1.43 - 9.67 CREA

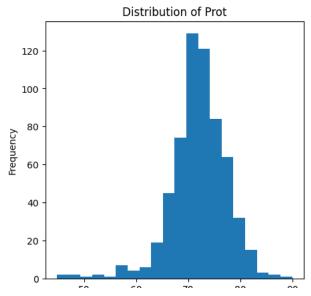


Range of values for Crea: 8.0 - 1079.1 GGT





Range of values for Ggt: 4.5 - 650.9



from scipy import stats

print(clean_data.head())

```
# Calculate z-scores for the "price" variable
z_scores = stats.zscore(pd.to_numeric(df["GGT"],errors="coerce"))
```

Set a threshold for outliers (e.g., z-score > 3 or < -3) threshold = 3

5.95 6.15 147.3 491.0

58.3

66.4

72.3

55.7

399.5

273.7

400.3

650.9

3.6

3.92

4.88

6.3

Identify the outliers
outliers = df[abs(z_scores) > threshold]

Remove the outliers from the dataset
clean_data = df[abs(z_scores) <= threshold]</pre>

Display the outliers and cleaned dataset
print("Outliers:")
print(outliers)
print("\nCleaned Dataset:")

Outl	iers:												
	Unnam	ed: 0			Catego	ry	Age	Sex	ALB	ALP	ALT	AST	\
205		206		0=B1	ood Don	or	50	m	42.2	145.0	27.5	37.9	
533		534	0s=sus	pect Bl	ood Don	or	47	m	22.5	124.0	79.5	46.7	
538		539	0s=sus	pect Bl	ood Don	or	74	m	20.3	84.0	22.8	43.0	
539		540	0s=sus	pect Bl	ood Don	or	59	f	19.3	208.2	325.3	146.6	
558		559		1=	Hepatit	is	56	m	37.0	114.0	27.8	324.0	
559		560		1=	Hepatit	is	58	m	43.0	99.1	12.2	63.2	
593		594		3=	Cirrhos	is	51	m	39.0	66.0	29.6	185.0	
598		599		3=	Cirrhos	is	58	m	31.0	143.1	7.0	181.8	
602		603		3=	Cirrhos	is	61	m	39.0	102.9	27.3	143.2	
610		611		3=	Cirrhos	is	62	f	32.0	416.6	5.9	110.3	
	BIL	CHE	CHOL	CREA	GGT	PR	TO						
205	4.5	13.71	8.8	103.0	239.0	73	.1						
533	2.3	6.83	4.3	170.0	345.6	58	.6						
538	5.7	4.91	3.19	52.0	218.3	47	.8						
539	6.9	5.33	4.72	32.0	295.6	53	.1						
558	67.0	5.75	3.09	97.7	392.2	77	.3						

79.4

78.1

73.4

Cleaned Dataset:

2.00

3.29

5.38

5.57

559 13.0

593 19.0

598 58.0

610 50.0

602 15.0

Category Age Sex ALB ALP ALT AST BIL CHE \

```
0
             0=Blood Donor
                                               7.7 22.1
                                                           7.5
                                                                6.93
           1
                            32
                                 m 38.5 52.5
1
             0=Blood Donor
                            32
                                 m
                                   38.5
                                        70.3
                                              18.0 24.7
                                                           3.9
                                                               11.17
                                m 46.9 74.7
2
             0=Blood Donor
                            32
                                               36.2 52.6
                                                          6.1
                                                                8.84
3
           4
             0=Blood Donor
                            32
                                m 43.2 52.0
                                               30.6 22.6 18.9
                                                                7.33
4
           5
             0=Blood Donor
                            32
                                 m 39.2
                                         74.1
                                               32.6 24.8
                                                           9.6
                                                                9.15
```

```
CHOL
        CREA
               GGT PROT
  3.23
0
        106.0
              12.1 69.0
   4.8
         74.0
              15.6
                    76.5
2
   5.2
         86.0
              33.2 79.3
3
                    75.7
  4.74
         80.0
              33.8
  4.32
         76.0
              29.9
                   68.7
```

<----->

#----code

Add more cells if required

Summarizing your analysis and observations

<----->

Can you explore the correlations between features and the diagnosis of hepatitis C? Are there any strong correlations or dependencies?

df.info

```
<bound method DataFrame.info of</pre>
                                    Unnamed: 0
                                                                        ALB
                                                                               ALP
                                                                                      ALT
                                                                                            AST
                                                                                                  BIL \
                                                    Category Age Sex
a
             1 0=Blood Donor
                                    m 38.5
                                              52.5
                                                      7.7
                                                            22.1
                                                                   7.5
1
             2 0=Blood Donor
                                32
                                    m 38.5
                                              70.3
                                                     18.0
                                                            24.7
                                                                   3.9
2
             3
                0=Blood Donor
                                32
                                    m
                                       46.9
                                               74.7
                                                     36.2
                                                            52.6
                                                                   6.1
3
                0=Blood Donor
                                32
                                       43.2
                                              52.0
                                                     30.6
                                                            22.6
                                                                  18.9
                                    m
4
             5 0=Blood Donor
                                32
                                    m 39.2
                                              74.1
                                                     32.6
                                                            24.8
                                                                   9.6
610
           611
                  3=Cirrhosis
                                62
                                       32.0
                                             416.6
                                                      5.9
                                                           110.3
                                                                  50.0
                  3=Cirrhosis
611
           612
                                64
                                    f
                                       24.0
                                             102.8
                                                      2.9
                                                            44 4
                                                                  20.0
612
           613
                  3=Cirrhosis
                                64
                                    f
                                       29.0
                                              87.3
                                                      3.5
                                                            99.0
                                                                  48.0
           614
                  3=Cirrhosis
                                46
                                    f 33.0
613
                                               NA
                                                     39.0
                                                            62.0
614
           615
                  3=Cirrhosis
                                59
                                     f 36.0
                                                NA 100.0
                                                            80.0 12.0
      CHE
          CHOL
                  CREA
                          GGT PROT
0
     6.93
           3.23
                 106.0
                         12.1
                               69.0
                  74.0
1
    11.17
            4.8
                         15.6
                               76.5
2
     8.84
            5.2
                  86.0
                         33.2
                               79.3
3
      7.33
           4.74
                  80.0
                         33.8
                               75.7
4
           4.32
                         29.9
                              68.7
     9.15
                  76.0
610
     5.57
            6.3
                  55.7
                        650.9
                              71.3
611
     1.54
           3.02
                  63.0
                        35.9
612
     1.66
           3.63
                  66.7
                         64.2 82.0
613
     3.56
            4.2
                  52.0
                         50.0
                              71.0
     9.07
            5.3
                  67.0
                         34.0
```

[615 rows x 14 columns]>

df.head()

	Unnamed:	0	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT	7
0		1	0=Blood Donor	32	m	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0	
1		2	0=Blood Donor	32	m	38.5	70.3	18.0	24.7	3.9	11.17	4.8	74.0	15.6	76.5	
2		3	0=Blood Donor	32	m	46.9	74.7	36.2	52.6	6.1	8.84	5.2	86.0	33.2	79.3	
3		4	0=Blood Donor	32	m	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7	
4		5	0=Blood Donor	32	m	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7	

selected_columns = ["Age","ALB", "ALP", "ALT", "AST","BIL","CHE","CHOL","CREA","GGT","PROT"]
subset_df = df[selected_columns]
subset_df.head()

	Age	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	32	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0
1	32	38.5	70.3	18.0	24.7	3.9	11.17	4.8	74.0	15.6	76.5
2	32	46.9	74.7	36.2	52.6	6.1	8.84	5.2	86.0	33.2	79.3
3	32	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7
4	32	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7

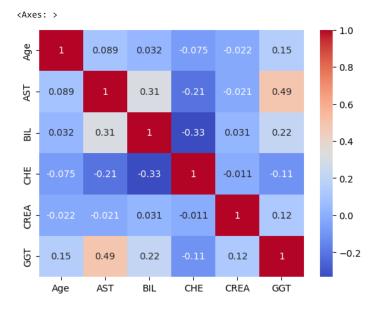
correlation_matrix = subset_df.corr()
correlation_matrix

<ipython-input-33-bda98bf6fb1c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr i
 correlation_matrix = subset_df.corr()

	Age	AST	BIL	CHE	CREA	GGT
Age	1.000000	0.088666	0.032492	-0.075093	-0.022296	0.153087
AST	0.088666	1.000000	0.312231	-0.208536	-0.021387	0.491263
BIL	0.032492	0.312231	1.000000	-0.333172	0.031224	0.217024
CHE	-0.075093	-0.208536	-0.333172	1.000000	-0.011157	-0.110345
CREA	-0.022296	-0.021387	0.031224	-0.011157	1.000000	0.121003
GGT	0.153087	0.491263	0.217024	-0.110345	0.121003	1.000000

import seaborn as sns

Create a heatmap of the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")



Summarizing your analysis and observation

▼ TASK 2 - Classification/Regression

Perform following steps on the same dataset which you used for EDA.

- Data Preprocessing (as per requirement)
- · Feature Engineering
- Split dataset in train-test (80:20 ratio)
- · Model selection
- Model training
- · Model evaluation
- · Fine-tune the Model
- Make predictions

Summarize your model's performance by evaluation metrices

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_csv("/content/HepatitisCdata.csv")
data.head(5)
```

	Unnamed:	Category	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	1	0=Blood Donor	32	m	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0
1	2	0=Blood Donor	32	m	38.5	70.3	18.0	24.7	3.9	11.17	4.80	74.0	15.6	76.5
2	3	0=Blood	32	m	46.9	74.7	36.2	52.6	6.1	8.84	5.20	86.0	33.2	79.3
4														

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

```
Unnamed: 0
               0
Category
               0
Age
               0
Sex
ALB
               1
ALP
              18
ALT
               1
               0
AST
BIL
               0
CHE
               0
CHOL
              10
CREA
               0
GGT
               0
PROT
               1
dtype: int64
```

 $from \ sklearn.model_selection \ import \ train_test_split$

Create the Random Forest Classifier

```
# Separate the target variable from the features
target = data['Category']
features = data.drop('Category', axis=1)

# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

from sklearn.ensemble import RandomForestClassifier
```

```
model = RandomForestClassifier()
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.model selection import train test split
from sklearn.impute import SimpleImputer
import pandas as pd
# Load the dataset
data=pd.read_csv("/content/HepatitisCdata.csv")
# Convert 'Sex' column to numerical values
data = pd.get_dummies(data, columns=['Sex'], drop_first=True)
# Separate the target variable from the features
target = data['Category']
features = data.drop('Category', axis=1)
# Perform missing value imputation
imputer = SimpleImputer(strategy='mean')
imputed_features = pd.DataFrame(imputer.fit_transform(features), columns=features.columns)
# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(imputed_features, target, test_size=0.2, random_state=42)
# Create the Random Forest Classifier
model = RandomForestClassifier()
# Train the model
model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = model.predict(X_test)
# Evaluate the model
report = classification_report(y_test, y_pred)
print(report)
```

	precision	recall	f1-score	support
0=Blood Donor	0.99	1.00	0.99	96
0s=suspect Blood Donor	1.00	0.33	0.50	3
1=Hepatitis	0.80	0.89	0.84	9
2=Fibrosis	0.62	0.83	0.71	6
3=Cirrhosis	1.00	0.78	0.88	9
accuracy			0.95	123
macro avg	0.88	0.77	0.79	123
weighted avg	0.96	0.95	0.95	123

from sklearn.metrics import classification_report

Make predictions on the test set
y_pred = model.predict(X_test)

Evaluate the model
report = classification_report(y_test, y_pred)
print(report)

	precision	recall	f1-score	support
0=Blood Donor 0s=suspect Blood Donor	0.99 1.00	1.00 0.33	0.99 0.50	96 3
1=Hepatitis	0.80	0.89	0.84	9
2=Fibrosis	0.62	0.83	0.71	6
3=Cirrhosis	1.00	0.78	0.88	9
266119261			0.95	123
accuracy			0.95	123
macro avg	0.88	0.77	0.79	123
weighted avg	0.96	0.95	0.95	123

```
from sklearn.model_selection import GridSearchCV
# Define the hyperparameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10]
}
# Create the GridSearchCV object
grid_search = GridSearchCV(model, param_grid, cv=5)
# Perform grid search to find the best hyperparameters
grid_search.fit(X_train, y_train)
# Get the best model with tuned hyperparameters
best_model = grid_search.best_estimator_
     /usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 4 mc
       warnings.warn(
    4
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
# Display the performance summary
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
     Accuracy: 0.9512195121951219
     Precision: 0.9590269047020368
     Recall: 0.9512195121951219
     F1-score: 0.9491240026643128
```

×