



Data Collection and Preprocessing Phase

Date	6 th june 2024
Team ID	SWTID1720175375
Project Title	Prediction and analysis of liver patient data using ML
Maximum Marks	6 Marks

Data Overview

RangeIndex: 583 entries, 0 to 582 Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype
0	Age	583 non-null	int64
1	Gender	583 non-null	object
2	Total_Bilirubin	583 non-null	float64
3	Direct_Bilirubin	583 non-null	float64
4	Alkaline_Phosphotase	583 non-null	int64
5	Alamine_Aminotransferase	583 non-null	int64
6	Aspartate_Aminotransferase	583 non-null	int64
7	Total_Protiens	583 non-null	float64
8	Albumin	583 non-null	float64
9	Albumin_and_Globulin_Ratio	579 non-null	float64
10	Dataset	583 non-null	int64

dtypes: float64(5), int64(5), object(1)

memory usage: 50.2+ KB

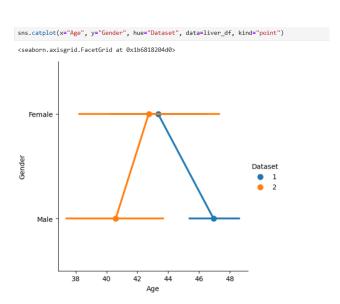
Univariate Analysis:





	Age	Gender	Total_Bilirubin	Direct_Bilirubin	${\bf Alkaline_Phosphotase}$	${\bf Alamine_Aminot ransferase}$	${\bf Aspartate_Aminot ransferase}$	Total_Protiens	Albumin
count	583.000000	583	583.000000	583.000000	583.000000	583.000000	583.000000	583.000000	583.000000
unique	NaN	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	NaN	Male	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	NaN	441	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	44.746141	NaN	3.298799	1.486106	290.576329	80.713551	109.910806	6.483190	3.141852
std	16.189833	NaN	6.209522	2.808498	242.937989	182.620356	288.918529	1.085451	0.795519
min	4.000000	NaN	0.400000	0.100000	63.000000	10.000000	10.000000	2.700000	0.900000
25%	33.000000	NaN	0.800000	0.200000	175.500000	23.000000	25.000000	5.800000	2.600000
50%	45.000000	NaN	1.000000	0.300000	208.000000	35.000000	42.000000	6.600000	3.100000
75%	58.000000	NaN	2.600000	1.300000	298.000000	60.500000	87.000000	7.200000	3.800000
max	90.000000	NaN	75.000000	19.700000	2110.000000	2000.000000	4929.000000	9.600000	5.500000

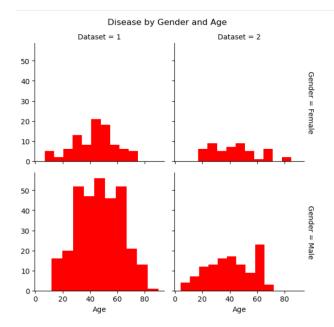
Bivariate Analysis:

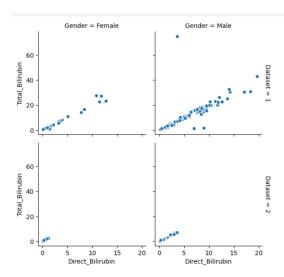


Age seems to be a factor for liver disease for both male and female genders





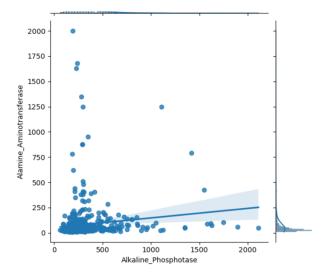




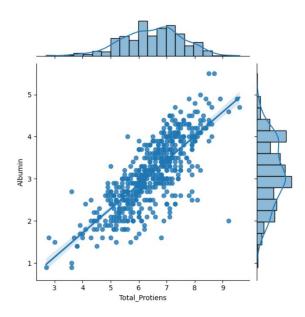
• There seems to be direct relationship between Total_Bilirubin and Direct_Bilirubin. We have the possibility of removing one of this feature.







No linear correlation between Alkaline_Phosphotase and Alamine_Aminotransferase







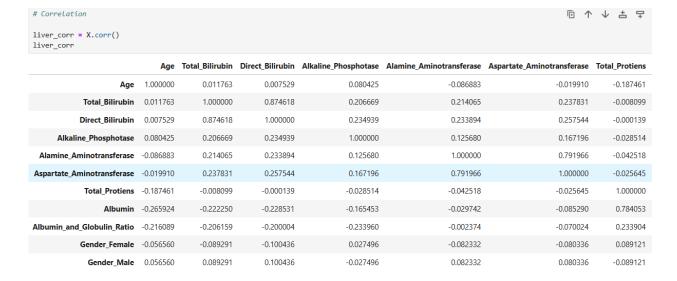
Observation:

From the above jointplots and scatterplots, we find direct relationship between the following features:

- Direct_Bilirubin & Total_Bilirubin
- Aspartate_Aminotransferase & Alamine_Aminotransferase
- Total_Protiens & Albumin
- · Albumin_and_Globulin_Ratio & Albumin

Hence, we can very well find that we can omit one of the features. I'm going to keep the follwing features:

- Total_Bilirubin
- · Alamine_Aminotransferase
- Total_Protiens
- · Albumin_and_Globulin_Ratio
- Albumin



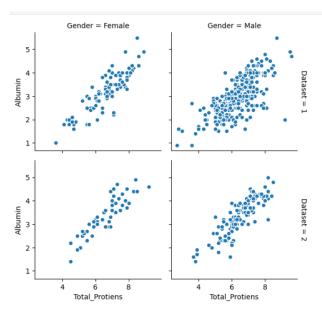
High Correlation between:

- Total_Protiens & Albumin
- Alamine_Aminotransferase & Aspartate_Aminotransferase
- Direct_Bilirubin & Total_Bilirubin
- There is some correlation between Albumin_and_Globulin_Ratio and Albumin. But its not as high as Total_Protiens & Albumin

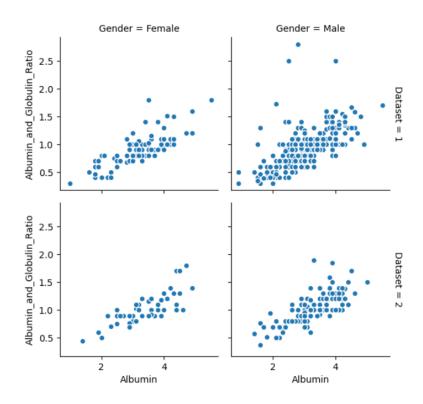




Multivariate Analysis:



• There is linear relationship between Total_Protiens and Albumin and the gender. We have the possibility of removing one of this feature.



• There is linear relationship between Albumin_and_Globulin_Ratio and Albumin. We have the possibility of removing one of this feature.





Anomalies:

Replaced Null values with mean value.

Removed duplicate values.

```
liver_df["Albumin_and_Globulin_Ratio"] = liver_df.Albumin_and_Globulin_Ratio.fillna(liver_df['Albumin_and_Globulin_Ratio'].mean())
```

Loading Data:

```
#Read the training & test data
# liver_df = pd.read_csv('/content/liver_patient.csv')
import types
import pandas as pd
liver_df= pd.read_csv('liver.csv')
liver_df.head()
liver_df.info()
```

Handling Missing Data:

```
liver_df["Albumin_and_Globulin_Ratio"] = liver_df.Albumin_and_Globulin_Ratio.fillna(liver_df['Albumin_and_Globulin_Ratio'].mean())
```

Data Transformation:

```
from sklearn.preprocessing import LabelEncoder
```

```
pd.get_dummies(liver_df['Gender'], prefix = 'Gender').head()
```

```
X=StandardScaler().fit_transform(x)
```

Feature Engineering:

```
pd.get_dummies(liver_df['Gender'], prefix = 'Gender').head()

liver_df = pd.concat([liver_df,pd.get_dummies(liver_df['Gender'], prefix = 'Gender')], axis=1)

liver_df['Dataset'].replace(2,0,inplace=True)
```





```
liver_df['Gender_Female'].replace({True:1,False:0},inplace=True)
liver_df['Gender_Male'].replace({True:1,False:0},inplace=True)
```