# ARIGNAR ANNA GOVT ARTS & SCIENCE COLLEGE, VILLUPURAM – 605 602.



### DEPARTMENT OF COMPUTER SCIENCE

### **MACHINE LEARNING WITH PYTHON**

**Project Title**: A Review of Liver Patient Analysis Method using Machine

Learning

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### **Abstract**

Around a million deaths occur due to liver diseases globally. There are several traditional methods to diagnose liver diseases, but they are expensive.

Early prediction of liver disease would benefit all individuals prone to liver diseases by providing early treatment. As technology is growing in health care, machine learning significantly affects health care for predicting conditionsat early stages. This study finds how accurate machine learning in predicting liver disease.

This present study introduces the liver disease prediction (LDP) method in predicting liver disease that can be utilised by health professionals, stakeholders, students and researchers. Five algorithms, namely Support Vector Machine (SVM), Naïve Bayes, K-Nearest Neighbors (K-NN), Linear Discriminant Analysis (LDA), and Classification and Regression Trees (CART), are selected. The accuracy is compared to uncover the best classification method for predicting liver disease using R and Python. From the results, Random Forest Classifier obtains the best accuracy with 67.7%, and the Decision Tree Classifier achieved 61.1% accuracy, which is above the acceptable level of accuracy and can be considered for liver disease prediction.

### <u>Introduction</u>

In this project we will analyse the parameters of various classification algorithms and compare their predictive accuracies so as to find out the best classifier for determining the liver disease. This project compares various classification algorithms such as Random Forest, Logistic Regression, KNN and ANN Algorithm with an aim to identify the best technique. Based on this study, Random Forest with the highest accuracy outperformed the other algorithms and can be further utilised in the prediction of liver disease and can be recommended to the Liver. According to World Health Organization (WHO) report in 2018, the number of deaths due to liver diseases is around one million and ranked 11th in the world with a critical number of fatalities (World Total Deaths, n.d.). Unnoticed at the initial stages, these symptoms are only visible when the disease turns chronic. However, even though the liver is partially infected, it can still function (Devikanniga et al., 2020).

Diagnosis of liver diseases can be divided into three stages i.e., the first stage is liver inflammation, the second is liver scarring (cirrhosis), and the final stage is liver cancer or failure. Since these scenarios are present in liver disease, early prediction is significant to provide better health for New Zealanders. If liver disease is diagnosed early, there will be a chance of early treatment and control of deaths due to liver diseases (Arbain & Balakrishnan, 2019). But when the liver fails to function, few treatments are available except liver transplantation (Shaheamlung et al., 2020), which is very expensive, particularly in New Zealand (Hepatitis C, 2021). Apparently, in New Zealand, 35 -40% of the population are not diagnosed with Hepatitis C at the early stages because of the asymptomatic behaviour of liver disease. Unfortunately, most of these individuals do not know the risks linked to liver disease. Due to the asymptomatic behaviour and higher costs of liver disease treatment, it is essential to prevent or diagnose early for better treatment.

### <u>Purpose</u>

Liver function tests can be used to: Screen for liver infections, such as hepatitis. Monitor the progression of a disease, such as viral or alcoholic hepatitis, and determine how well a treatment is working. Measure the severity of a disease, particularly scarring of the liver (cirrhosis)

### Problem Definetion & Design Thinking

### **Empathy Map**



# Idea Prioritization & Brainstorm map Policy purposes aleased Marked prioritization Marke

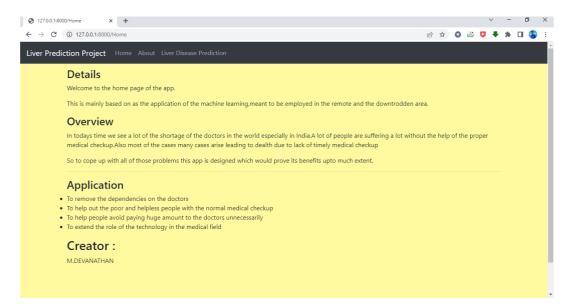
### Result:

Liver Patients analysis using machine learning can provide accurate and realiable results for the diagnosis, prognosis, and treatment of liver disease. Machine learning algorithm can analyse large amounts of patients data and identify patterns that may be difficult for human experts to detect.

## Source code: Milestone 1: Home.html

```
<!DOCTYPE html>
<html lang="en">
<head>
<title>Home</title>
</head>
<style>
#main-footer
{color: #FFFFFF;
font-family: "Segoe UI";
background: #2B2B2B;
text-align: center;
margin-top: 108px;
padding: 16px;
bottom: 8px;}
</style>
<div class= "container">
<div class="col-md-8">
{% with messages = get flashed messages(with categories=true) %}
{% if messages %}
{% for category, message in messages %}
<div class="alert alert-{{ category }}">
{{ message }}
</div>
{% endfor %}
{% endif %}
{% endwith %}
</div>
<h3 style="margin-top: 5%;">Details </h3>
Welcome to the home page of the app.
This is mainly based on as the application of the machine learning, meant to be employed in the remote and the
downtrodden area.
<h3>Overview</h3>
In todays time we see a lot of the shortage of the doctors in the world especially in India. A lot of people are suffering a
lot without the help of the proper medical checkup. Also most of the cases many cases arise leading to dealth due to lack
of timely medical checkup
So to cope up with all of those problems this app is designed which would prove its benefits upto much extent.
<hr>
<h3>Application</h3>
To remove the dependencies on the doctors
To help out the poor and helpless people with the normal medical checkup
To help people avoid paying huge amount to the doctors unnecessarily
To extend the role of the technology in the medical field
<h2>Creator :</h2>
       M.DEVANATHAN
>
</div>
</body>
</html>
```

### Output:



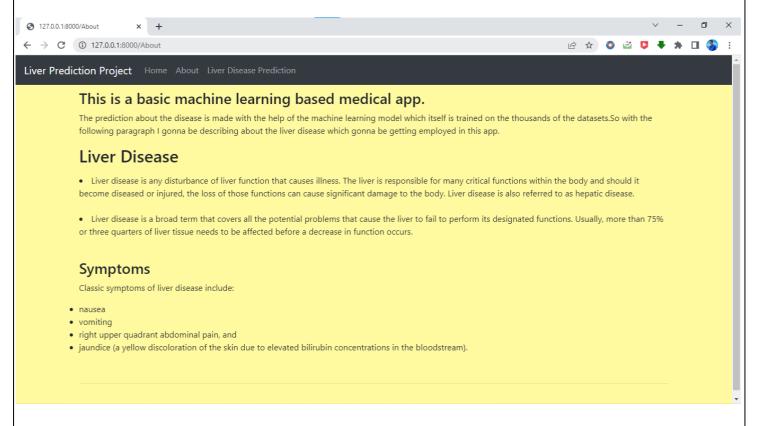
### **About.html**

```
<html>
<body>
<style>
#main-footer
color: #FFFFFF;
font-family: "Segoe UI";
background: #2B2B2B;
text-align: center;
margin-top: 75px;
padding: 16px;
bottom: 8px;
.img_holder img{
max-width: 100%; max-height: 100%;
.btn-file {
position: relative;
overflow: hidden;
.btn-file input[type=file] {
position: absolute;
top: 0;
right: 0;
min-width: 100%;
min-height: 100%;
font-size: 100px;
text-align: right;
filter: alpha(opacity=0);
opacity: 0;
outline: none;
background: white;
cursor: inherit;
```

display: block;

```
</style>
<div class="container">
<h1>About : </h1>
<h3>This is a basic machine learning based medical app.</h3>
The prediction about the disease is made with the help of the machine learning model which itself is trained on the
thousands of the datasets. So with the following paragraph I gonna be describing about the liver disease which gonna be
getting employed in this app.
<h2>Liver Disease</h2>
Liver disease is any disturbance of liver function that causes illness. The liver is responsible for many critical
functions within the body and should it become diseased or injured, the loss of those functions can cause significant
damage to the body. Liver disease is also referred to as hepatic disease.
Liver disease is a broad term that covers all the potential problems that cause the liver to fail to perform its
designated functions. Usually, more than 75% or three quarters of liver tissue needs to be affected before a decrease in
function occurs.<br>
<h3>Symptoms</h3>
Classic symptoms of liver disease include:
nausea
vomiting
right upper quadrant abdominal pain, and 
jaundice (a yellow discoloration of the skin due to elevated bilirubin concentrations in the bloodstream).
<br>
<hr>
<br>
</body>
</htm>
```

### Output:



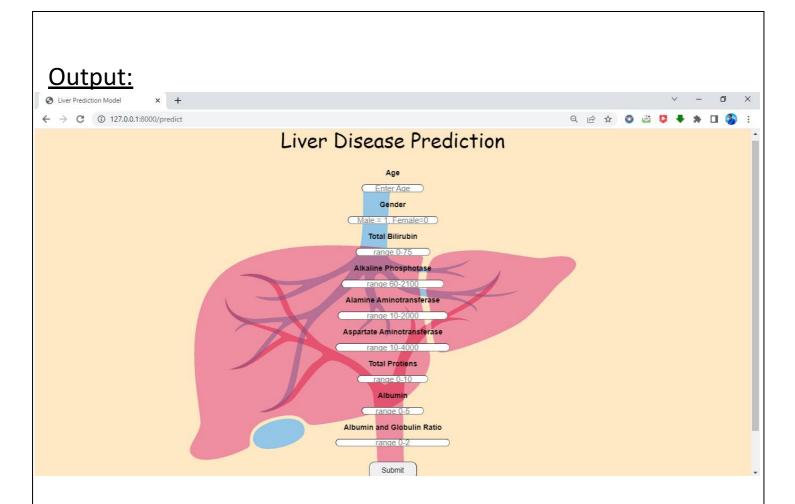
### <u>liverprediction.html</u>

```
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8">
<title>Liver Prediction Model</title>
</head>
<body>
<div class="container">
<h2 class='container-heading'><span class="heading font">Liver Disease Prediction</span></h2>
</div>
<div class="ml-container">
<form action="{{ url for('predict') }}" method="POST">
<br>
<h3>Age</h3>
<input id="first" name="Age" placeholder="Enter Age" required="required">
<br>
<h3>Gender</h3>
<input id="second" name="Gender" placeholder="Male = 1, Female=0" required="required">
<br>
<h3>Total Bilirubin</h3>
<input id="third" name="Total_Bilirubin" placeholder="range 0-75" required="required">
<br>
<h3>Alkaline Phosphotase</h3>
<input id="fourth" name="Alkaline_Phosphotase" placeholder="range 60-2100" required="required">
<br>
<h3>Alamine Aminotransferase</h3>
<input id="fifth" name="Alamine_Aminotransferase" placeholder="range 10-2000" required="required">
<br>
<h3>Aspartate Aminotransferase</h3>
<input id="sixth" name="Aspartate_Aminotransferase" placeholder="range 10-4000" required="required">
<br>
<h3>Total Protiens</h3>
<input id="seventh" name="Total_Protiens" placeholder="range 0-10" required="required">
<br>
<h3>Albumin</h3>
<input id="eight" name="Albumin" placeholder="range 0-5" required="required">
<br>
<h3>Albumin and Globulin Ratio</h3>
<input id="ninth" name="Albumin_and_Globulin_Ratio" placeholder="range 0-2" required="required">
<br>
<br>
<button id="sub" type="submit ">Submit</button>
<br>
<br>
```

```
Dear Crush DB 2023
</form>
</div>
<style>
/* Background Image */
body
background-image:url("https://raw.githubusercontent.com/SagarDhandare/Liver-Disease-Prediction-
Project/main/Images/Liver.jpg");
height: 100%;
/* Center and scale the image nicely */
background-position: center;
background-repeat: no-repeat;
background-size: 100% 100%;
/* Color */
body{
font-family: Arial, Helvetica, sans-serif;
text-align: center;
margin: 0;
padding: 0;
width: 100%;
height: 100%;
display: flex;
flex-direction: column;
/* Heading Font */
.container-heading{
margin: 0;
.heading_font{
color: #black;
font-family: 'Pacifico', cursive;
font-size: 50px;
font-weight: normal;
```

```
/* Box */
#first {
border-radius: 14px;
height: 15px;
width: 150px;
font-size: 20px;
text-align: center;
#second {
border-radius: 14px;
height: 15px;
width: 220px;
font-size: 20px;
text-align: center;
#third {
border-radius: 14px;
height: 15px;
width: 180px;
font-size: 20px;
text-align: center;
#fourth {
border-radius: 14px;
height: 15px;
width: 250px;
font-size: 20px;
text-align: center;
#fifth {
border-radius: 14px;
height: 15px;
width: 270px;
font-size: 20px;
text-align: center;
#sixth {
border-radius: 14px;
height: 15px;
width: 280px;
font-size: 20px;
text-align: center;
```

```
#seventh {
border-radius: 14px;
height: 15px;
width: 170px;
font-size: 20px;
text-align: center;
#eight {
border-radius: 14px;
height: 15px;
width: 150px;
font-size: 20px;
text-align: center;
#ninth {
border-radius: 14px;
height: 15px;
width: 280px;
font-size: 20px;
text-align: center;
/* Submit Button */
#sub {
width: 120px;
height: 43px;
text-align: center;
border-radius: 14px;
font-size: 18px;
<link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
</style>
</body>
</html>
```



### Nochange.html

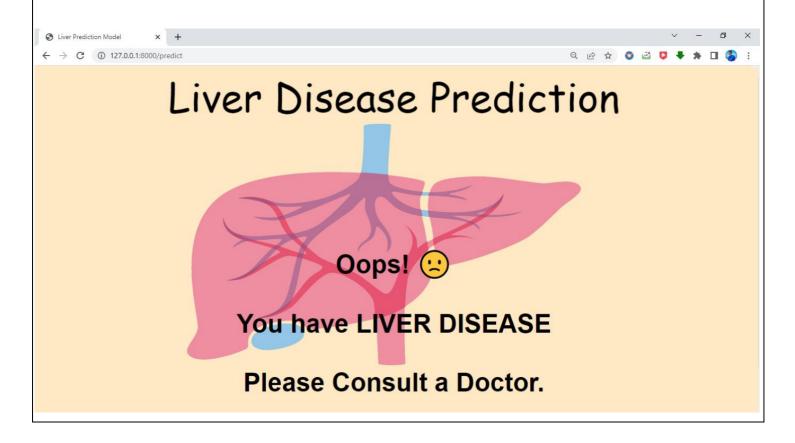
```
<!DOCTYPE html>
```

- <html lang="en">
- <head>
- <meta charset="UTF-8">
- <meta name="viewport" content="width=device-width, initialscale=1.0">
- <title>Liver Disease Result</title>
- </head>
- <body>
- <div class="container">
- <form action="/data\_predict" method="post">
- <h2 class='container-heading'><span class="heading\_font">Liver
  Disease Prediction</span></h2>

```
<!-- Result -->
<div class="results">
<h1><span class='danger'>Oops! <a href="mailto:left">Cops! <a href="mailto:left">Cops!
DISEASE <br>>Please Consult a Doctor.</span></h1>
<style>
/* Background Image */
body
background-
image:url("https://raw.githubusercontent.com/SagarDhandare/Li
ver-Disease-Prediction-Project/main/Images/Liver.jpg");
height: 100%;
/* Center and scale the image nicely */
background-position: center;
background-repeat: no-repeat;
background-size: 100% 100%;
 /* Color */
body{
font-family: Arial, Helvetica, sans-serif;
text-align: center;
margin: 0;
padding: 0;
width: 100%;
height: 100%;
display: flex;
flex-direction: column;
 /* Heading Font */
 .container-heading{
```

```
margin: 0;
}
.heading_font{
color: #black;
font-family: 'Pacifico', cursive;
font-size: 50px;
font-weight: normal;
}
k = "stylesheet"
href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
</style>
</body>
</html>
```

### Output:



### **Application:**

- Diagnosis: Liver patients analysis can be used to diagnose liver diseases such as cirrhosis, hepatitis, and Livercancer, by analysing various biomarkers such as liver enyzmes, bilirubin, and albumin, doctors can determine the health of the liver and diagnose any underlying diseases.
- Treatment: Liver patients analysis can also to monitor the effectiveness of treatments for liver diseases. By regulary analysing liver function tests and other biomarkers, doctors can achieve optimal results

### **Conclusion:**

- Since the liver disease is not easy to diagnose, given the delicate nature of its signs, this research is in determining the algorithms that have better accuracy in predicting this dreadful disease.
- Once the dataset is selected, the preprocessing step is conducted by replacing the missing values and balancing the dataset.
- After that, using R, five different supervised learning methods are applied (i.e., SVM, Naïve Bayes, K-NN, LDA, and CART), and the accuracy with confusion matrix metrics are recorded.

- In this study, the autoencoder with 3-layers achieved an accuracy of 92.1%, slightly higher than K-NN due to its ability to ascertain overlapping features better than conventional K-NNs. Most of the algorithms are more than the acceptable level of accuracy, which is 75%.
- The results from this study would be able to assist health professionals and relevant stakeholders in the early detection of liver disease.

### Future scope

- In this paper, we proposed and built a machine learning based on a hybrid classifier to be used as a classification model for liver diseases diagnosis to improve performance and experrts to identify the chances of disease and conscious orescription of further treatment healthcare and examination.
- In future work, the use of fast datasets technique like apache hadoop or spark can be incorporated with this technique. In addition to this, we can use distributed refined algorithm like forest tree implement in apache hadoop to increase scalability and efficieny.

# Appendix:

# Jupyter File

### **Mliestone 2:**

```
In [1]: import pandas as pd
          import numpy as np
          import seaborn as sns
          import matplotlib.pyplot as plt
          from matplotlib import rcParams
         from scipy import stats
In [2]: data=pd.read_csv("indian_liver_patient.csv")
          display(data.head())
         display(data.tail())
              Age Gender Total_Bilirubin Direct_Bilirubin Alkaline_Phosphotase Alamine_Aminotransferase Aspartate_Aminotransferase Total_Protiens Albumin Albumin
              65 Female
                                     0.7
                                                    0.1
                                                                         187
                                                                                                   16
                                                                                                                                           6.8
                                                                                                                                                    3.3
               62
                     Male
                                                    41
                                                                                                                                                    3.3
               62
                     Male
                                     7.3
                                                                         490
                                                                                                   60
                                                                                                                              68
                                                                                                                                           7.0
                                                    0.4
                                                                                                   14
                                                                                                                              20
                                                                                                                                                    3.4
                                                                         195
                                                                                                   27
                                                                                                                              59
              72
                     Male
                                     3.9
                                                    2.0
                                                                                                                                           7.3
                                                                                                                                                    2.4
                            Total_Bilirubin Direct_Bilirubin Alkaline_Phosphotase Alamine_Aminotransferase Aspartate_Aminotransferase
                                                                                                                                   Total Protiens Albumin
                    Gender
                                                      0.1
                                                                           500
                                                                                                                                             5.9
           578
                 60
                       Male
                                       0.5
                                                                                                     20
                                                                                                                                                       1.6
           579
                 40
                       Male
                                       0.6
                                                      0.1
                                                                                                     35
                                                                                                                                31
                                                                                                                                              6.0
                                                                                                                                                       3.2
           580
                 52
                       Male
                                       8.0
                                                      0.2
                                                                           245
                                                                                                     48
                                                                                                                                49
                                                                                                                                              6.4
                                                                                                                                                      3.2
           581
                       Male
                                       1.3
                                                      0.5
                                                                           184
                                                                                                     29
                                                                                                                                32
                                                                                                                                              6.8
                                                                                                                                                      34
           582
                       Male
```

```
In [3]: data.shape
Out[3]: (583, 11)
In [4]: data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 583 entries, 0 to 582
        Data columns (total 11 columns):
             Column
                                          Non-Null Count Dtype
         0
                                          583 non-null
                                                          int64
             Age
             Gender
                                          583 non-null
                                                          object
             Total_Bilirubin
                                          583 non-null
                                                          float64
             Direct Bilirubin
                                          583 non-null
                                                          float64
             Alkaline Phosphotase
                                          583 non-null
                                                          int64
             Alamine_Aminotransferase
                                          583 non-null
                                                          int64
                                                          int64
             Aspartate Aminotransferase
                                          583 non-null
             Total Protiens
                                          583 non-null
                                                          float64
                                          583 non-null
                                                          float64
             Albumin
             Albumin_and_Globulin_Ratio
                                         579 non-null
                                                          float64
         10
                                          583 non-null
            Dataset
                                                          int64
        dtypes: float64(5), int64(5), object(1)
        memory usage: 50.2+ KB
```

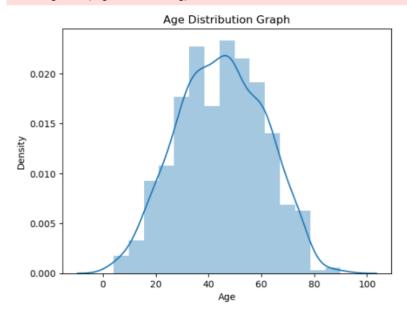
```
In [5]: data.isnull().any()
    Out[5]: Age
                                              False
              Gender
                                              False
             Total_Bilirubin
Direct_Bilirubin
                                              False
                                              False
             Alkaline_Phosphotase
                                              False
             Alamine_Aminotransferase
                                              False
             Aspartate_Aminotransferase
                                             False
              Total_Protiens
                                              False
             Albumin
                                             False
              Albumin_and_Globulin_Ratio
                                              True
                                              False
             dtype: bool
    In [6]: data.isnull().sum()
    Out[6]: Age
                                             0
              Gender
                                              0
             Total_Bilirubin
                                             a
                                             0
             Direct Bilirubin
             Alkaline_Phosphotase
              Alamine_Aminotransferase
             Aspartate_Aminotransferase
                                             0
              Total_Protiens
                                             0
             Albumin
             Albumin_and_Globulin_Ratio
             Dataset
             dtype: int64
In [7]: data['Albumin_and_Globulin_Ratio'].fillna(data['Albumin_and_Globulin_Ratio'].mode()[0],inplace=True)
         data.isnull().sum()
                                          0
Out[7]: Age
         Gender
                                          0
         Total_Bilirubin
                                          0
         Direct_Bilirubin
                                          0
         Alkaline_Phosphotase
                                          0
         Alamine Aminotransferase
                                          0
         Aspartate_Aminotransferase
                                          0
         Total_Protiens
                                          0
         Albumin
                                          0
         Albumin_and_Globulin_Ratio
         Dataset
                                          0
         dtype: int64
In [8]: from sklearn.preprocessing import LabelEncoder
         lc = LabelEncoder()
         data['Gender']=lc.fit_transform(data['Gender'])
In [9]: data.describe()
Out[9]:
                              Gender Total_Bilirubin Direct_Bilirubin Alkaline_Phosphotase Alamine_Aminotransferase Aspartate_Aminotransferase Total_Protiens
                      Age
          count 583.000000 583.000000
                                         583.000000
                                                       583.000000
                                                                           583.000000
                                                                                                   583.000000
                                                                                                                            583.000000
                                                                                                                                         583.000000 58
          mean 44.746141
                            0.756432
                                          3.298799
                                                         1.486106
                                                                           290.576329
                                                                                                    80.713551
                                                                                                                            109.910806
                                                                                                                                           6.483190
                 16.189833
                             0.429603
                                          6.209522
                                                         2.808498
                                                                           242.937989
                                                                                                   182.620356
                                                                                                                            288.918529
                                                                                                                                           1.085451
            std
                                          0.400000
                                                         0.100000
                                                                                                    10.000000
                                                                                                                                           2.700000
           min
                  4 000000
                             0.000000
                                                                            63.000000
                                                                                                                            10.000000
           25% 33 000000 1 000000
                                       0.800000
                                                         0.200000
                                                                           175 500000
                                                                                                    23 000000
                                                                                                                            25 000000
                                                                                                                                           5.800000
```

### Milestone 3:

```
In [10]: sns.distplot(data['Age'])
    plt.title('Age Distribution Graph')
    plt.show()
```

C:\Users\DEVIL\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar fle xibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

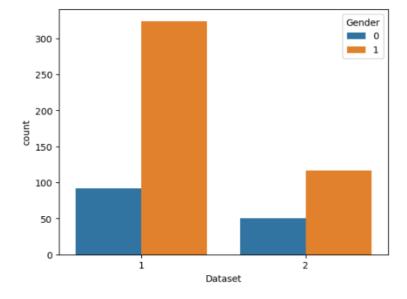


### In [11]: sns.countplot(data['Dataset'], hue=data['Gender'])

C:\Users\DEVIL\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke yword will result in an error or misinterpretation.

warnings.warn(

Out[11]: <AxesSubplot:xlabel='Dataset', ylabel='count'>



In [12]: plt.figure(figsize=(10,7)) sns.heatmap(data.corr(),annot=True) Out[12]: <AxesSubplot:> - 1.0 0.057 0.012 0.0075 -0.27Age -1 0.08 -0.087-0.02-0.19-0.22-0.14Gender 0.057 1 0.089 0.1 -0.027 0.082 0.08 -0.089 -0.094 -0.0041 -0.082 - 0.8 Total\_Bilirubin -0.012 0.089 1 0.87 0.24 -0.0081 -0.22 -0.21 -0.22 Direct Bilirubin - 0.0075 0.1 0.87 0.26 0.00014 -0.23 -0.2 - 0.6 1 -0.25Alkaline\_Phosphotase -0.08 -0.027 0.21 0.23 1 0.13 -0.029 -0.17 -0.23 -0.18 0.4 0.79 Alamine\_Aminotransferase --0.0870.082 0.21 0.23 0.13 1 -0.043-0.03 -0.0027 -0.16 1 0.026 -0.085 -0.07 Aspartate\_Aminotransferase --0.02 0.08 0.24 0.26 0.17 0.79 -0.15 0.2 -0.089 -0.0081-0.00014 -0.029 -0.043 Total Protiens --0.19-0.026 1 0.78 0.23 0.035 Albumin --0.27 -0.094 -0.22 -0.23 -0.17 -0.03 -0.085 1 0.0 Albumin\_and\_Globulin\_Ratio --0.22 -0.0041 -0.21 -0.2 -0.23 -0.0027 -0.07 0.23 1 0.16 -0.14 -0.082 -0.22 -0.25 -0.18 -0.16 -0.15 0.035 Dataset 0.16 0.16 1 Bilirubin Phosphotase Aminotransferase Albumin Globulin Ratio Gender Aminotransferase Direct\_Bilirubin Dataset Total In [13]: X=data.iloc[:,:-1] y=data.Dataset In [14]: from sklearn.preprocessing import scale X\_scaled=pd.DataFrame (scale(X), columns=X.columns) In [15]: X\_scaled.head() Out[15]: Gender Total\_Bilirubin Direct\_Bilirubin Alkaline\_Phosphotase Alamine\_Aminotransferase Aspartate\_Aminotransferase Total\_Protiens Age Albumin 0 1.252098 -1.762281 -0.418878 -0.493964 -0.428715 -0.354885 -0.318393 0.292120 0.198969 1 1.088837 0.587448 1.225171 1.430423 1.682629 -0.091599 -0.034333 0.937588 0.073157 2 1.088837 0.587448 0.644919 0.931508 0.821588 -0.113522 -0.145186 0.478533 0.198989 3 0.819356 0.567446 -0.370523 -0.387054 -0.447314 -0.365626 -0.311465 0.292120 0.324781 4 1.684839 0.567446 0.098902 0.183135 -0.393756 -0.294379 -0.176363 0.753153 -0.933340 In [16]: from sklearn.model\_selection import train\_test\_split X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled,y, test\_size=0.2,random\_state=12) In [17]: from imblearn.over\_sampling import SMOTE smote = SMOTE() In [18]: y\_train.value\_counts() Out[18]: 1 Name: Dataset, dtype: int64 In [19]: X\_train\_smote, y\_train\_smote = smote.fit\_resample(X\_train, y\_train) In [20]: y\_train\_smote.value\_counts() Out[20]: 1 328 328 Name: Dataset, dtype: int64

### **MILESTONE 4:**

weighted avg

0.80

0.61

0.63

117

```
In [21]: from sklearn.ensemble import RandomForestClassifier
           from sklearn.metrics import accuracy_score
           from sklearn.metrics import classification_report
           model1=RandomForestClassifier()
           model1.fit(X_train_smote, y_train_smote)
y_predict = model1.predict(X_test)
rfc1=accuracy_score(y_test,y_predict)
           rfc1
           pd.crosstab(y_test, y_predict)
print(classification_report (y_test, y_predict))
                            precision
                                          recall f1-score support
                        1
                                  0.82
                                              0.73
                                                           0.77
                                                                         88
                                              0.52
                accuracy
                                                           0.68
                                                                        117
                                  0.60
                                              0.62
               macro avg
                                                           0.61
                                                                        117
           weighted avg
                                                           0.69
In [22]: from sklearn.tree import DecisionTreeClassifier
           model4 = DecisionTreeClassifier()
model4.fit(X_train_smote, y_train_smote)
y_predict=model4.predict(X_test)
           dtc1=accuracy_score(y_test,y_predict)
           dtc1
           pd.crosstab(y_test,y_predict)
print(classification_report(y_test, y_predict))
                            precision
                                           recall f1-score support
                                  0.77
                        1
                                             0.69
                                                           0.73
                                                                         88
                        2
                                 0.29
                                              0.38
                                                          0.33
                                                                         29
                accuracy
                                                           0.62
                                                                        117
                                 0.53
                                             0.54
               macro avg
                                                           0.53
                                                                        117
           weighted avg
                                  0.65
                                              0.62
                                                           0.63
                                                                        117
In [23]: from sklearn.neighbors import KNeighborsClassifier
           model2=KNeighborsClassifier()
           model2.fit(X_train_smote, y_train_smote)
           y_predict = model2.predict(X_test)
            knn1=(accuracy_score (y_test, y_predict))
           pd.crosstab(y_test,y_predict)
           print(classification_report (y_test, y_predict))
                            precision recall f1-score support
                         1
                                  0.83
                                           0.56
                                                         0.67
                                                                        88
                                                        0.44
                                  0.33
                                              0.66
                                                           0.58
                                                                       117
                accuracv
               macro avg
                                  0.52
                                              0.61
                                                           0.55
                                                                        117
                                              0.58
           weighted avg
                                 0.71
                                                           0.61
                                                                        117
           C:\Users\DEVIL\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other reduction func
           tions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, th is behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.
              mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
In [24]: from sklearn.linear_model import LogisticRegression
           model5=LogisticRegression()
           model5.fit(X_train_smote, y_train_smote)
           y_predict=model5.predict(X_test)
           logi1=accuracy_score(y_test, y_predict)
           logi1
           pd.crosstab(y_test,y_predict)
           print(classification_report (y_test, y_predict))
                            precision recall f1-score support
                                  0.94
                         1
                                              0.51
                                                           0.66
                                                                         88
                                  0.38
                                              0.90
                                                           0.53
                accuracy
                                                           0.61
                                                                        117
               macro avg
                                  0.66
                                              0.70
                                                           0.60
                                                                        117
```

```
In [25]: import tensorflow.keras
       from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense
In [26]: classifier=Sequential()
        classifier.add(Dense(units=100,activation='relu',input dim=10))
        classifier.add(Dense(units=50,activation='relu'))
        classifier.add(Dense(units=1,activation='sigmoid'))
        classifier.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
        model_history=classifier.fit(X_train,y_train,batch_size=100,validation_split=0.2,epochs=100)
       Epoch 1/100
       4/4 [=========] - 6s 292ms/step - loss; 1.0012 - accuracy; 0.0027 - val loss; 0.8586 - val accuracy; 0.063
       Epoch 2/100
       4/4 [=========] - 0s 42ms/step - loss: 0.7599 - accuracy: 0.2339 - val loss: 0.6218 - val accuracy: 0.5319
       Epoch 3/100
       4/4 [=========] - 0s 39ms/step - loss: 0.5569 - accuracy: 0.6478 - val loss: 0.4276 - val accuracy: 0.6809
        Epoch 4/100
        Epoch 5/100
       4/4 [=========] - 0s 40ms/step - loss: 0.2408 - accuracy: 0.7097 - val loss: 0.0926 - val accuracy: 0.6809
       Epoch 6/100
       4/4 [=========] - 0s 39ms/step - loss: 0.0933 - accuracy: 0.7097 - val loss: -0.0684 - val accuracy: 0.680
       Epoch 7/100
       4/4 [=========] - 0s 38ms/step - loss: -0.0543 - accuracy: 0.7097 - val loss: -0.2299 - val accuracy: 0.68
       Epoch 8/100
       4/4 [==========] - 0s 40ms/step - loss: -0.1996 - accuracy: 0.7097 - val_loss: -0.3923 - val_accuracy: 0.68
       Epoch 9/100
       4/4 [=========] - 0s 40ms/step - loss: -0.3512 - accuracy: 0.7097 - val loss: -0.5588 - val accuracy: 0.68
       Epoch 10/100
       4/4 [=========] - 0s 37ms/step - loss: -0.5028 - accuracy: 0.7097 - val loss: -0.7356 - val accuracy: 0.68
       09
        Epoch 11/100
       4/4 [=========] - Os 41ms/step - loss: -0.6673 - accuracy: 0.7097 - val loss: -0.9190 - val accuracy: 0.68
        99
       Epoch 12/100
       4/4 [==========] - 0s 40ms/step - loss: -0.8241 - accuracy: 0.7097 - val_loss: -1.1146 - val_accuracy: 0.68
       Epoch 13/100
        4/4 [==============] - 0s 45ms/step - loss: -1.0050 - accuracy: 0.7097 - val loss: -1.3224 - val accuracy: 0.68
```

```
Epoch 14/100
-712313.8125 - val_accuracy: 0.7234
Epoch 15/100
-721993.8125 - val_accuracy: 0.7234
Epoch 16/100
-731739.5625 - val accuracy: 0.7234
Epoch 17/100
-741573.6875 - val accuracy: 0.7234
Epoch 18/100
-751650.8125 - val accuracy: 0.7234
Epoch 19/100
-761723.0000 - val_accuracy: 0.7234
Epoch 20/100
-771933.6875 - val_accuracy: 0.7234
Epoch 21/100
-782164.2500 - val_accuracy: 0.7234
Epoch 22/100
-792485.2500 - val accuracy: 0.7234
Epoch 23/100
```

```
-803042.0625 - val accuracy: 0.7234
Epoch 24/100
-813523.7500 - val_accuracy: 0.7234
Epoch 25/100
-824129.3750 - val_accuracy: 0.7234
Epoch 26/100
-834718.0625 - val_accuracy: 0.7234
Epoch 27/100
-845578.3750 - val accuracy: 0.7234
Epoch 28/100
-856461.6250 - val_accuracy: 0.7234
Epoch 29/100
-867335.2500 - val_accuracy: 0.7234
Epoch 30/100
-878283.5625 - val_accuracy: 0.7234
Epoch 31/100
-889272.2500 - val accuracy: 0.7234
```

```
Epoch 32/100
val loss: -900362.7500 - val accuracy: 0.7234
Epoch 33/100
val_loss: -911565.0000 - val_accuracy: 0.7234
Epoch 34/100
val_loss: -922823.0000 - val_accuracy: 0.7234
Epoch 35/100
val_loss: -934481.6250 - val_accuracy: 0.7234
Epoch 36/100
val loss: -945996.4375 - val accuracy: 0.7234
Epoch 37/100
val_loss: -957543.7500 - val_accuracy: 0.7234
Epoch 38/100
val_loss: -969030.5625 - val_accuracy: 0.7234
Epoch 39/100
val_loss: -980694.3125 - val_accuracy: 0.7234
Epoch 40/100
val_loss: -992526.8125 - val_accuracy: 0.7234
Epoch 41/100
val_loss: -1004365.9375 - val_accuracy: 0.7234
Epoch 42/100
```

```
val_loss: -1016444.1875 - val_accuracy: 0.7234
Epoch 43/100
val loss: -1028518.8125 - val accuracy: 0.7234
Epoch 44/100
val_loss: -1040690.8750 - val_accuracy: 0.7234
Epoch 45/100
val loss: -1052845.2500 - val accuracy: 0.7234
Epoch 46/100
val_loss: -1065299.1250 - val_accuracy: 0.7234
Epoch 47/100
val loss: -1077800.1250 - val accuracy: 0.7234
Epoch 48/100
val_loss: -1090211.3750 - val_accuracy: 0.7234
Epoch 49/100
val loss: -1102746.2500 - val accuracy: 0.7234
Epoch 50/100
val_loss: -1115452.1250 - val_accuracy: 0.7234
Epoch 51/100
val_loss: -1128213.5000 - val_accuracy: 0.7234
Epoch 52/100
val_loss: -1141175.3750 - val_accuracy: 0.7234
Epoch 53/100
```

```
val_loss: -1153975.8750 - val_accuracy: 0.7234
Epoch 54/100
val loss: -1166885.2500 - val accuracy: 0.7234
Epoch 55/100
val_loss: -1179737.3750 - val_accuracy: 0.7234
Epoch 56/100
val loss: -1193090.7500 - val accuracy: 0.7234
Epoch 57/100
val loss: -1206648.1250 - val accuracy: 0.7234
Epoch 58/100
val loss: -1220226.7500 - val accuracy: 0.7234
Epoch 59/100
val loss: -1233714.5000 - val accuracy: 0.7234
Epoch 60/100
val loss: -1247228.3750 - val accuracy: 0.7234
Epoch 61/100
val_loss: -1260871.1250 - val_accuracy: 0.7234
Epoch 62/100
val_loss: -1274690.7500 - val_accuracy: 0.7234
Epoch 63/100
val_loss: -1288476.2500 - val_accuracy: 0.7234
Epoch 64/100
```

```
val_loss: -1302399.7500 - val_accuracy: 0.7234
Epoch 65/100
val loss: -1316549.5000 - val accuracy: 0.7234
Epoch 66/100
val_loss: -1330783.8750 - val_accuracy: 0.7234
Epoch 67/100
val loss: -1344791.1250 - val accuracy: 0.7234
Epoch 68/100
val_loss: -1359089.2500 - val_accuracy: 0.7234
Epoch 69/100
val loss: -1373541.0000 - val accuracy: 0.7234
Epoch 70/100
val_loss: -1388008.6250 - val_accuracy: 0.7234
Epoch 71/100
val loss: -1402453.5000 - val accuracy: 0.7234
Epoch 72/100
val_loss: -1417268.3750 - val_accuracy: 0.7234
Epoch 73/100
val_loss: -1432073.5000 - val_accuracy: 0.7234
Epoch 74/100
val_loss: -1447196.8750 - val_accuracy: 0.7234
Epoch 75/100
```

```
val_loss: -1462295.5000 - val_accuracy: 0.7234
Epoch 76/100
val loss: -1477444.3750 - val accuracy: 0.7234
Epoch 77/100
val_loss: -1492718.0000 - val_accuracy: 0.7234
Epoch 78/100
val loss: -1508000.1250 - val accuracy: 0.7234
Epoch 79/100
val_loss: -1523874.7500 - val_accuracy: 0.7234
Epoch 80/100
val loss: -1539401.7500 - val accuracy: 0.7234
Epoch 81/100
val_loss: -1555277.7500 - val_accuracy: 0.7234
Epoch 82/100
val loss: -1571173.1250 - val accuracy: 0.7234
Epoch 83/100
val_loss: -1586805.2500 - val_accuracy: 0.7234
Epoch 84/100
val_loss: -1602683.8750 - val_accuracy: 0.7234
Epoch 85/100
val_loss: -1618731.8750 - val_accuracy: 0.7234
Epoch 86/100
```

```
val_loss: -1634839.8750 - val_accuracy: 0.7234
Epoch 87/100
val loss: -1650720.6250 - val accuracy: 0.7234
Epoch 88/100
val_loss: -1667040.0000 - val_accuracy: 0.7234
Epoch 89/100
val loss: -1683222.5000 - val accuracy: 0.7234
Epoch 90/100
val loss: -1699956.3750 - val accuracy: 0.7234
Epoch 91/100
val loss: -1716632.1250 - val accuracy: 0.7234
Epoch 92/100
val loss: -1733106.0000 - val accuracy: 0.7234
Epoch 93/100
val loss: -1749683.3750 - val accuracy: 0.7234
Epoch 94/100
val_loss: -1766571.7500 - val_accuracy: 0.7234
Epoch 95/100
val_loss: -1783625.3750 - val_accuracy: 0.7234
Epoch 96/100
val_loss: -1800817.8750 - val_accuracy: 0.7234
Epoch 97/100
```

```
val loss: -1818068.7500 - val accuracy: 0.7234
Epoch 98/100
val loss: -1835457.7500 - val accuracy: 0.7234
Epoch 99/100
val_loss: -1853025.7500 -
          0.6809
          Epoch 100/100
          4/4 [========= ] - 0s 35ms/step - loss: -824.5608 - accuracy: 0.7097 - val_loss: -897.3958 - val_accuracy:
    In [27]: model4.predict([[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]])
          C:\Users\DEVIL\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but DecisionT
          reeClassifier was fitted with feature names
           warnings.warn(
    Out[27]: array([2], dtype=int64)
    In [28]: model1.predict([[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]])
          C:\Users\DEVIL\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but RandomFor
          estClassifier was fitted with feature names
           warnings.warn(
    Out[28]: array([1], dtype=int64)
    In [29]: classifier.save("liver.h5")
    In [30]: y_pred = classifier.predict(X_test)
          4/4 [======] - 0s 5ms/step
    In [31]: y_pred
          y_pred = (y_pred > 0.5)
          y_pred
    Out[31]: array([[ True],
                True],
                True],
                True],
                True],
                True],
                True],
                True],
                Truel,
                True],
                True],
                True],
                True],
```

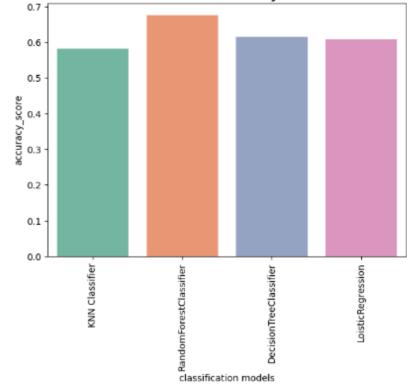
```
In [32]: def predict_exit(sample_value):
             sample_value=np.array(sample_value)
             sample_value=sample_value.reshape(1,-1)
             sample_value=scale(sample_value)
             return classifier.predict(sample_value)
In [33]: sample_value=[[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]]
         if predict_exit(sample_value)>0.5:
            print('Prediction: Liver Patient')
             print('Prediction: Healthy')
         1/1 [======] - Os 184ms/step
         Prediction: Liver Patient
In [34]: acc_smote=[['KNN Classifier',knn1],['RandomForestClassifier',rfc1],['DecisionTreeClassifier',dtc1],['LoisticRegression',logi1]]
         Liverpatient_pred=pd.DataFrame(acc_smote,columns=['classification models','accuracy_score'])
         Liverpatient pred
Out[34]:
             classification models accuracy_score
         0
                  KNN Classifier
                                   0.581197

    RandomForestClassifier

                                   0.675214

    DecisionTreeClassifier

                               0.615385
                LoisticRegression
In [35]: plt.figure(figsize=(7,5))
         plt.xticks(rotation=90)
         plt.title('Classification models & accuracy scores after SMOTE',fontsize=18)
         sns.barplot(x="classification models",y="accuracy_score", data=Liverpatient_pred,palette="Set2")
Out[35]: <AxesSubplot:title={'center':'Classification models & accuracy scores after SMOTE'}, xlabel='classification models', ylabel='ac
         curacy_score'>
        Classification models & accuracy scores after SMOTE
```



### **MILESTONE 5:**

```
In [37]: model.feature_importances_
Out[37]: array([8.12026859, 0.024727 , 0.10979189, 0.10245196, 0.11654257, 0.11399954, 0.11870815, 0.09126762, 0.1023186 , 0.09992409])
In~[38]:~ \\ dd=pd.DataFrame(model.feature\_importances\_,index=X.columns).sort\_values(0,ascending=False)
Out[38]:
            Aspertate Amingtranaterase 0.118708
                 Alkaline l'hosphotase 0.116543
              Alamine Amingtransferage 0.114000
                       lotel Bilirubin 0.109792
                       Direct Bilinubin 0.102452
                            Albumin 0.102319
           Albumin and Globulin Ratio 0.099924
           Total Probens 0.091268
                              Gender 0.024727
In [39]: dd.plot(kind="barh",figsize=(7,6))
plt.title("FEATURE IMPORTANCE",fontsize=14)
Out[39]: Text(0.5, 1.0, 'FEATURE IMPORTANCE')
                                                                   FEATURE IMPORTANCE
                                  Gender
                            Total_Protiens
            Albumin_and_Globulin_Ratio
                                 Albumin
                          Direct_Bilirubin
                           Total_Bilinubin
              Alamine_Aminotransferase
                    Alkaline_Phosphotase
            Aspartate_Aminotransferase
                                      Age
                                                      0.02
                                                                  0.04
                                                                                0.06
                                                                                            0.08
                                                                                                         0.10
                                                                                                                      0.12
```

In [48]: import joblib
 joblib.dump(model1,'ETC.pkl')

Out[48]: ['ETC.pk1']

```
Milestone 6:
 python file (app.p)
from flask import Flask,render_template,request
import numpy as np
import pickle
app=Flask(__name___,template_folder = 'template')
 @app.route('/')
def base():
  return render_template('base.html')
 @app.route('/Home')
def home():
  return render_template('home.html')
 @app.route('/About')
def about():
  return render_template('about.html')
 @app.route('/predict')
def index():
 return render_template("liverprediction.html")
 @app.route('/data_predict',methods = ['POST'])
def predict():
   age = request.form['age']
   gender=request.form['gender']
```

```
tb=request.form['tb']
  db=request.form['db']
  ap=request.form['ap']
  aa1=request.form['aa1']
  aa2=request.form['aa2']
  tp=request.form['tp']
  a=request.form['a']
  agr=request.form['agr']
  data =
[[float(age),float(gender),float(db),float(ap),float(aa1),float(aa2),float(t
p),float(a),float(agr)]]
  model = pickle.load(open('ETC.pkl','rb'))
  prediction = model.predict(data)[0]
  if(prediction==1) :
   return render_template('noChance.html',prediction='You have a
liver desease problem, You must and should consult a doctor. Take
care')
  else:
   return render template('chance.html', prediction='You dont have a
liver desease problem')
if __name__=='__main___':
 app.debug= True
 app.run(port=8000)
```

