LIVER CANCER PREDICTION

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ABSTRACT—The use of hybrid intelligence methodologies across several categories of cancer diagnosis and therapy is the main emphasis of this paper's thorough review on the detection of liver cancer. Highlighting the frequently utilized features, classifiers, techniques, essential ideas, and their related accuracy levels is the major goal of this review. Different machine learning algorithms, such as decision trees, support vector machines (SVM), neural networks, random forests, computer-aided detection, and genetic algorithms, are used in the field of cancer detection approaches. These methods demonstrate varied degrees of accuracy and have a substantial influence on how liver pictures are characterized. The article examines performance measures for a variety of solutions.

Keywords— Machine learning; MLP classifier; Cancer;

I. INTRODUCTION

Hepatic cancer, often known as liver cancer, is a kind of cancer that begins in the cells of the liver. The liver is a vital organ that helps in the digestion of fats, filters and processes blood and creates bile. It is in the right upper abdominal region. The two main types of liver cancer are primary liver cancer, which begins in the cells of the liver, and secondary liver cancer, which appears when cancer cells spread from one part of the body to the liver. Liver cancer is the one which has less survival rate. Numerous risk factors, such as chronic hepatitis B or C infection, excessive alcohol use, non-alcoholic fatty liver disease, obesity, and chemical exposure, contribute to the development of liver cancer. Constipation and fatigue might be symptoms of liver cancer. puffiness or discomfortjaundice (a yellowing of the skin and eyes), appetite loss, and weight loss. However, liver cancer may go undetected until it is well advanced. As liver cancer therapies, there are surgery, radiation therapy, chemotherapy, and targeted drug therapy options. The stage of cancer, the patient's overall health, and other factors can have an impact on the therapeutic option.

Preventive measures for liver cancer include obtaining a hepatitis B vaccination, diagnosing and treating hepatitis B or C infections, limiting alcohol use, keeping a healthy weight, and avoiding contact with toxic substances. Early detection is crucial for the effective treatment of liver cancer, therefore people who are at risk should talk to their doctor about screening options. Many Diagnostic techniques are there to detect liver cancer but the fact is that they cannot detect the cancer in its early stage. In

our proposed method we have suggested the framework to predict the cancer if a patient is suffering from common and severe symptoms.

II. BACKGROUND & LITERATURE REVIEW

In recent years, there has been notable progress in addressing the challenges associated with the study of gene expression data in cancer. Researchers have employed diverse mathematical and statistical methods to identify specific genes or gene pathways that are implicated in cancer development. These identified gene signatures have shown promise in enhancing cancer prediction capabilities.

Liver cancer accounts for a significant There is a global public health concern with the International Agency for Research on Cancer (IARC). According to the Global Cancer Observatory, there will be 905,677 cases reported and 830,180 fatalities worldwide in 2020. The bulk of liver cancer instances are seen in underdeveloped nations, where chronic viral hepatitis B or C infections are very common. Chronic viral hepatitis B or C infections, alcohol use, and non-alcoholic fatty liver disease (NAFLD) are significant risk factors for liver cancer. The stage of the malignancy at the time of diagnosis, which is evaluated by imaging tests like ultrasound, computed tomography (CT) scans, and MRI (magnetic resonance imaging), as well as hereditary variables and exposure to aflatoxins, are also important. Treatment options encompass surgical resection, liver transplantation, as well as non-surgical approaches such as ablation, embolization, and radiation therapy.

Significant advancements and improvements in the treatment of liver cancer, such as the creation of novel treatment modalities like targeted therapies and immunotherapies. However, the overall prognosis for liver cancer remains challenging, as it is often diagnosed at an advanced stage when treatment options are limited. Further research and improved early detection strategies are essential for improving outcomes in liver cancer patients The prognosis for liver cancer remains unfavorable, with a five-year survival rate of approximately 20%.Prevention and early detection have been demonstrated to be crucial in improving outcomes for liver cancer.

Key strategies for preventing liver cancer include hepatitis B vaccination, treatment of viral hepatitis, reduction of alcohol consumption, maintenance of a healthy weight, and regular screening for individuals at high risk. Liver cancer is a significant health issue characterized by a high mortality rate. Chronic viral hepatitis, The main causes of non-alcoholic fatty liver disease and alcohol usage include risk factors for liver cancer. Early detection and preventive measures are pivotal in enhancing outcomes for this disease. Liver cancer detection plays a vital role in its management, as early detection substantially increases the chances of successful treatment. A review of the literature on liver cancer detection reveals various methods, including imaging tests, blood tests, and biopsy. Imaging tests such as ultrasound, computed tomography (CT) scans, and magnetic resonance imaging (MRI) scans are commonly employed to detect liver cancer and determine its stage. These imaging tests can identify tumors or abnormal growths in the liver.

Blood tests can also assist in detecting liver cancer by measuring elevated liver enzymes and tumor markers. However, liver biopsy, which involves examining a small sample of liver tissue under a microscope, remains the most accurate method.

III. IMAGING TECHNIQUES FOR LIVER CANCER DETECTION

- HCC: The type of cancer of the liver that's diagnosed most frequently is hepatocellular carcinoma.
- AFP: As a marker for detecting and tracking liver cancer, alpha-fetoprotein, a protein generated by liver cancer cells.
- CT: computed tomography, an imaging technique employed to detect liver cancer by creating detailed cross-sectional images of liver.
- MRI: magnetic resonance imaging, another imaging method utilized for liver cancer detection, providing detailed images using magnetic fields and radio waves.
- PET: positron emission tomography, a type of imaging test that can detect liver cancer and other types of cancers by visualizing metabolic activity.
- NAFLD: Non-alcoholic fatty liver disease is defined by fat buildup in the liver and is associated with an elevated risk of liver cancer.
- HBV: hepatitis B virus, an infectious virus that can cause liver damage and heighten the risk of liver cancer.
- HCV: hepatitis C virus, another virus that can cause liver damage and increase the risk of liver cancer
- TACE: trans arterial chemoembolization, a treatment for liver cancer that involves injecting chemotherapy drugs directly into the tumor
- RFA: radiofrequency ablation, a treatment for liver cancer that uses heat to destroy cancer cells
- TACE-RFA: a combination of trans arterial chemoembolization and radiofrequency ablation, used to treat larger liver tumors.

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IV. METHODOLOGY

Figure 1 below shows the block diagram of proposed method to predict liver cancer using mlp classifier.

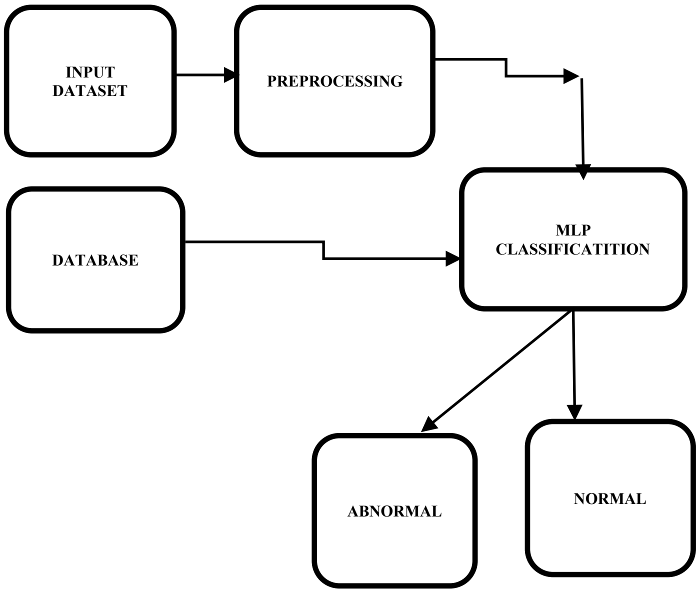

Fig.1. Block Diagram of Liver cancer prediction

Data Collection: Gather patient data, including personal and medical history, lifestyle habits, and genetic information. This data can be obtained through medical records, surveys, and genetic testing.

Data Preprocessing: Clean and preprocess the data, which may involve removing outliers, filling missing values, and transforming the data into a suitable format for analysis.

Firstly the data will the unwanted columns will be deleted. And then data will be scaled to because to bring the value to the nearest value.

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Model Selection: Choose an appropriate machine learning algorithm, The Multi-layer Perceptron (MLP) classifier, as its name suggests, is associated with a Neural Network. In contrast to other classification algorithms like Support Vector Machines or Naive Bayes Classifier, the MLP classifier relies on a layered structure.the figure 2 below shows the schematic diagram of MLP.

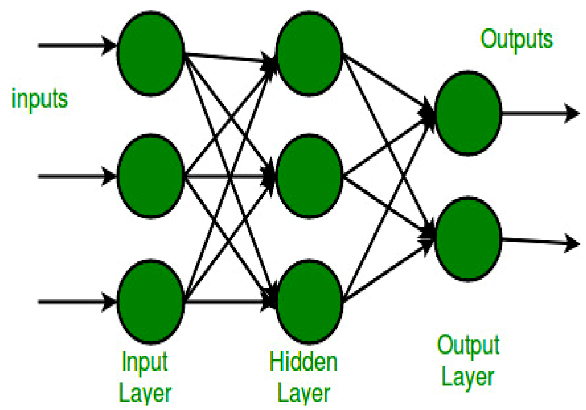

Fig.2. Schematic Diagram of MLP

The MLP classifier consists of multiple layers, typically referred to as functions or layers, forming a network denoted as

$$f(x) = f(3)(f(2)(f(1)(x))). \quad (1)$$

These layers are comprised of units that perform an affine transformation, which involves a linear sum of inputs. Mathematically, each layer can be represented as

$$y = f(WxT + b), \quad (2)$$

where W represents the weight matrix, x is the input vector, b denotes the bias vector, and f refers to the activation function applied to the linear sum. In summary, the MLP classifier utilizes a multi-layered structure with units that perform linear transformations and activation functions, ultimately enabling the network to learn complex patterns and make accurate classifications.

In MLP classifier for the binary classification of system following parameters need to be entered

```
mlp_clf = MLPClassifier(hidden_layer_sizes=(5,2),
        max_iter = 300,activation = 'relu',
                solver = 'adam')
```

Model Training: Train the model using the preprocessed data and selected features, and evaluate its performance using techniques such as cross-validation and hold out testing.

Model Optimization: Optimize the model parameters to achieve the best possible predictive accuracy.

Model Deployment: Deploy the model into a real- world setting, where it can be used to predict liver cancer risk in new patients.

Then finally after classification the system gives the result termed with Normal or abnormal liver and gives prediction for cancer.

V. RESULTS

The dataset used for the prediction of liver cancer is given below. Totally 500 dataset has been taken few samples are as shown.

TABLE 1:Dataset

Age	Gender	Total_ Bilirubin	Direct _Bilirubin	Alkaline _Phosphotase	Alamine_Amino transferase	Aspartate_Amin otransferase	Total_Protiens
65	Female	0.7	0.1	187	16	18	6.8
62	Male	10.9	5.5	699	64	100	7.5
62	Male	7.3	4.1	490	60	68	7
58	Male	1	0.4	182	14	20	6.8
72	Male	3.9	2	195	27	59	7.3
46	Male	1.8	0.7	208	19	14	7.6
26	Female	0.9	0.2	154	16	12	7
29	Female	0.9	0.3	202	14	11	6.7
17	Male	0.9	0.3	202	22	19	7.4
55	Male	0.7	0.2	290	53	58	6.8
57	Male	0.6	0.1	210	51	59	5.9
72	Male	2.7	1.3	260	31	56	7.4
64	Male	0.9	0.3	310	61	58	7
74	Female	1.1	0.4	214	22	30	8.1
61	Male	0.7	0.2	145	53	41	5.8
25	Male	0.6	0.1	183	91	53	5.5
38	Male	1.8	0.8	342	168	441	7.6
33	Male	1.6	0.5	165	15	23	7.3
40	Female	0.9	0.3	293	232	245	6.8
40	Female	0.9	0.3	293	232	245	6.8
51	Male	2.2	1	610	17	28	7.3
51	Male	2.9	1.3	482	22	34	7
62	Male	6.8	3	542	116	66	6.4
40	Male	1.9	1	231	16	55	4.3
63	Male	0.9	0.2	194	52	45	6
34	Male	4.1	2	289	875	731	5
57	Male	1	0.3	187	19	23	5.2
38	Female	2.6	1.2	410	59	57	5.6
38	Female	2.6	1.2	410	59	57	5.6
30	Male	1.3	0.4	482	102	80	6.9
17	Female	0.7	0.2	145	18	36	7.2
46	Female	14.2	7.8	374	38	77	4.3
48	Male	1.4	0.6	263	38	66	5.8
47	Male	2.7	1.3	275	123	73	6.2

Figure 3 below shows the gender value count graph for female patients with '1' as liver cancer and '0' as no liver cancer

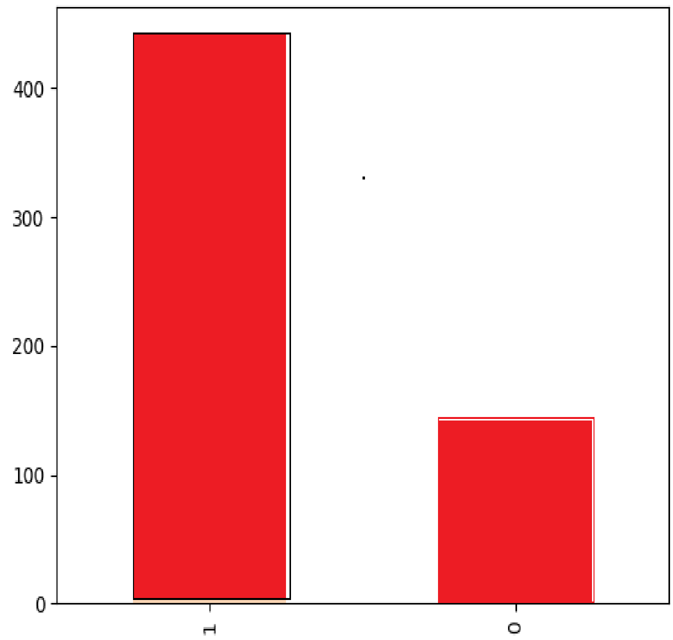

Fig. 3. Gender value count for female

Figure 3 below shows the gender value count graph for male patients with '1' as liver cancer and '0' as no liver cancer

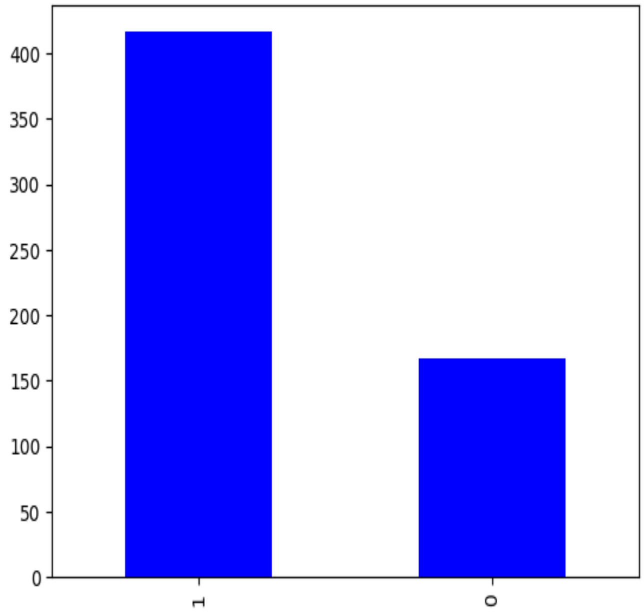

Fig. 4. Gender value count for female

A.

Relationship between Total_Bilirubin and Direct_Bilirubin as Shown in figure 5 below

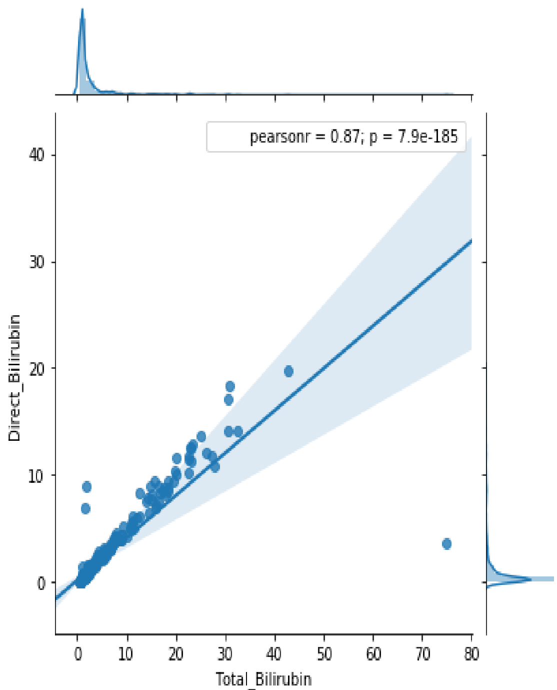

Fig. 5. Relationship between Total_Bilirubin and Direct_Bilirubin

For the same data set Figure 6 below shows the Linear relationship between Aspartate_Aminotransferase and Alamine_Aminotransferase

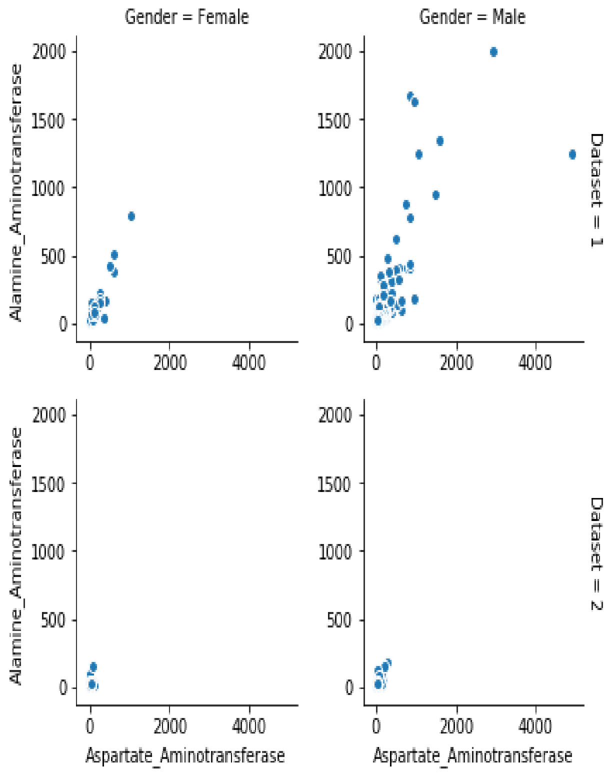

Fig..6. Linear relationship between Aspartate_Aminotransferase and Alamine_Aminotransferase and the gender

Correlation matrix is as shown below

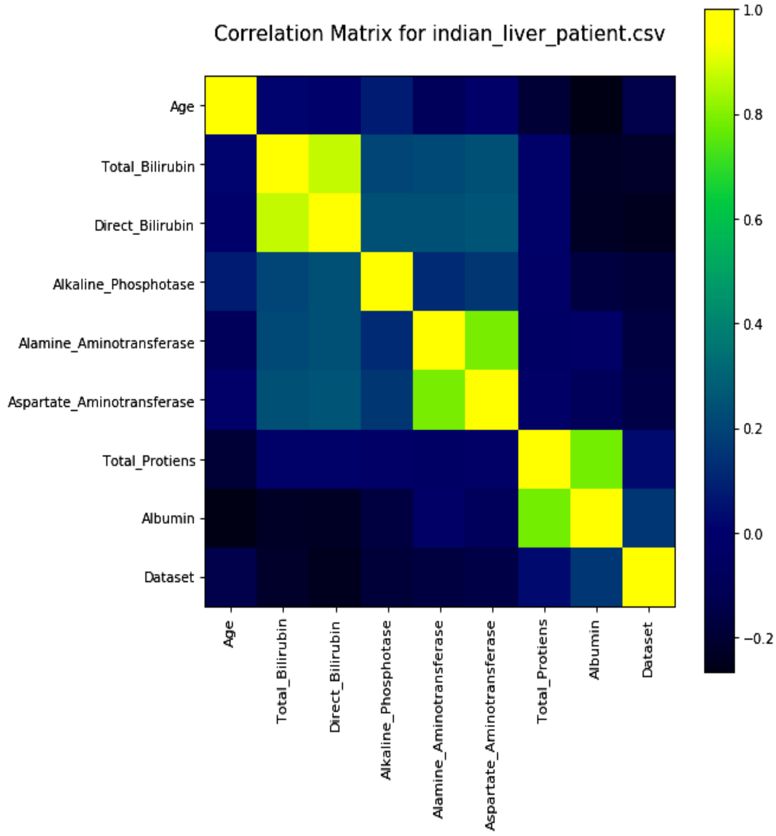

Fig. 7. Correlation matrix for liver cancer patients

VI. CONCULSION

Liver cancer continues to be a major worldwide health concern, posing significant challenges in terms of detection and prognosis, despite advancements in diagnosis and treatment. Current research efforts are dedicated to enhancing our understanding of liver cancer's underlying biology, devising innovative approaches for early detection, and identifying more efficacious treatment options. By persistently improving prevention strategies, early detection methods, and therapeutic interventions, the aim is to reduce the impact of liver cancer on patients and society in the coming years.

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