Machine Learning Algorithm Early Detection of Liver Cancer: A Review

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ABSTRACT
One of the most highly prevalent cancers today is liver cancer.The segmentation of a liver tumour is a critical step in making an early detection and recommending a treatment. It has always been tedious to segment data by hand, so cancer detection techniques now use a variety of machine learning algorithms, such as decision trees, Support Vector machine, artificial neural networks, random forests, Logistic Regressions and genetic algorithms. These algorithms are all used in the cancer detection process. The purpose of this review article is to conduct a comprehensive and comparative analysis of machine learning algorithms for diagnosing and predicting liver cancer in the medical field, which have already been used to predict liver disease by a number of authors, and to highlight the most frequently used features, classifiers, techniques, fundamental ideas, and accuracy.

Keywords
Machine Learning, Liver Cancer, Feature Selection, Accuracy

1. INTRODUCTION
The liver is the largest in the body, located above and to the left of the stomach and directly beneath the lung. It performs many vital functions such as the production of bile, metabolism, and absorption of bilirubin helps in blood clotting, metabolism of fats and carbohydrates, stores vitamins and minerals, produces albumin. The liver is a very complex organ, so that it can experience multiple problems. So, the consequences of the diseased liver can be perilous and it can lead to a variety of illnesses, including alcoholic liver disease, fascioliasis, cirrhosis, hepatitis, fatty liver disease, and liver cancer.[1] The below figure shows structure of liver in fig. 1.

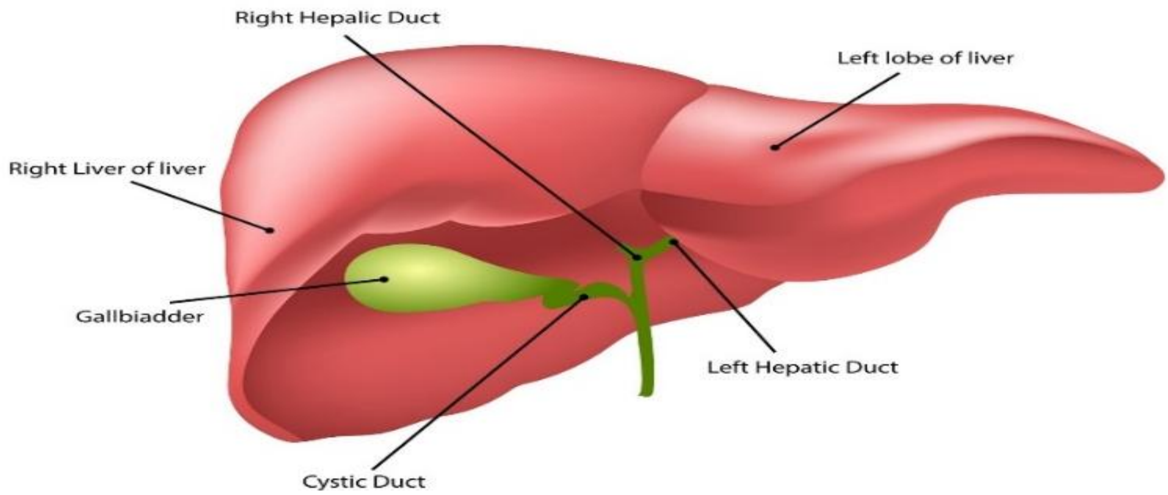

Fig 1:Structure of liver

The rate of incidence and death due to cancer of the liver has been increasing steadily. According to cancer statistics, there have been 18.1 million additional cancers diagnosed and 9.6 million cancer deaths in 2018. Asia accounts for over half among all cancer cases as well as more than half of cancer deaths worldwide, according to these figures. By 2020, liver cancer will rank sixth among all cancers diagnosed globally and would be the third largest cause of death.[2]Most of the time, liver cancer does not show any symptoms till the liver damage is extensive. But if any symptoms occur, they may include loss of weight and appetite, pain in upper abdominal or abdominal swelling, yellowing of the skin(jaundice), nausea, vomiting, etc. Liver cancer happens due to mutations in DNA, which results in cell growth in an Uncontrolled manner HBV and HCV infection, cirrhosis, inherited liver illnesses, diabetes, non-alcoholic fatty liver disease, aflatoxins exposure, and persistent alcoholism are all risk factors for liver cancer. As a result, early cancer detection and therapy are critical challenges.[3]Blood tests, liver biopsy, CT scans, MRI, ultrasounds can be done to detect liver disease or cancer. After inspecting all of these, doctors or practitioners decide whether is always a difficult task, as it requires experienced physicians and takes ample amount of time. Machine learning plays a vital function in disease diagnosis and treatments. It can help to extract valuable information from medical datasets and build a model toidentify the patients. For instance, various research has been conducted to determine the prevalence of liver problems in patients using machine learning and data mining techniques. [4][5]

Fig. 2: Progression of liver damage

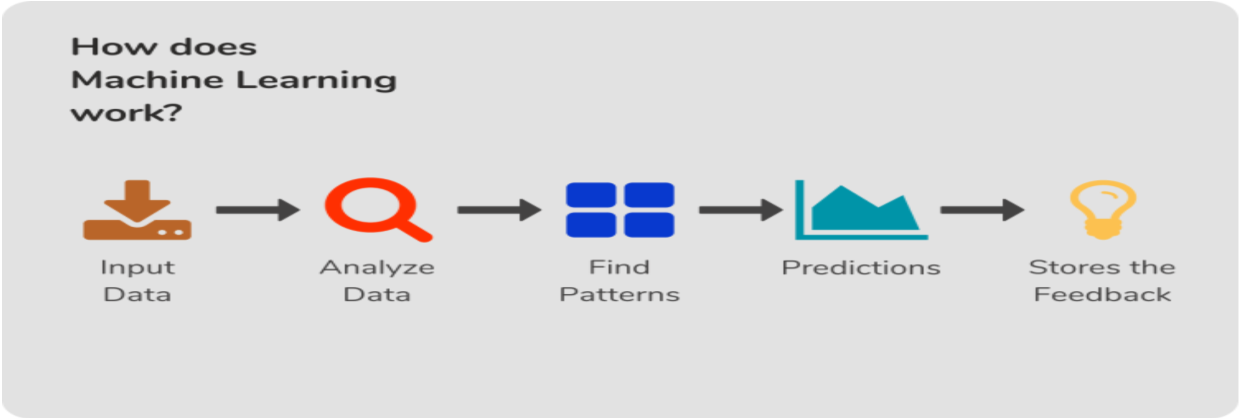

Fig. 3:Steps of Machine Learning Algorithm

2. MACHINE LEARNING ALGORITHMS

Machine learning employs algorithms in their most basic form, which study incoming data, make reasonable forecasts, and improve their operations. These algorithms generate more precise estimates as they are fed with additional data. We can classify Machine Learning Algorithms into three part that is supervised, semi-supervised and unsupervised.The base algorithm is trained in monitored machine learning techniques through a named training data set. Then, the unlabelled test data set is placed in the trained algorithm and categorized into like categories. Classification and regression problems can both be solved using supervised learning methods. In the first type of problem variable or the output can be categorized into group or classes, that is in classification, the output is always discrete in nature. For example, 'zero' or 'one' or 'unhealthy' and 'healthy.' In regression issues, the associated output variable is an exact value, such as an individual's risk of developing liver cancer. In the figure, the basic steps of Machine Learning have described.The generally used machine learning classification techniques for disease forecast are briefly described in the subsections below.

2.1. Logistic regression

It is a supervised technique for classification that is securely verified and it is an expansion of traditional regression.But it can only model binary variables that show the occurrence or non-occurrence of particular category events. Hence, we need to assign a threshold value to be used as a classifier to differentiate between two classes. For instance, let us say the expectation value of a data instance is more than 0.25, so if it comes below that, it will be under class A, otherwise class B.

2.2. Decision tree

It is among the oldest and best-known ML algorithms. Contains decision logic for classifying tree-structured data items such as tests and results. A node in a DT tree often has multiple levels, with the root node acting as the primary node. Each internal node represents an input variable or property test (at least one child).[6]
Continues the test and branching procedure until the leaf criteria is met. Finally, the leaf or terminal node represents the selection's outcome. As a result, they are easy to understand and learn and are used in various medical diagnostic procedures. Furthermore,when traversing the tree for classification, all test results for each node provide sufficient knowledge to make expert decisions about the class in the sample.[7]

2.3. Support Vector Màchine

SVM is a machine learning supervised learning technique that uses a mathematical approach to handle classification and regression issues. By using hyperplanes, SVM divides data points plotted in an n-dimensional space into categories. To classify data points, the margin between the hyperplanes must be increased. There are a variety of kernels for separating linear and nonlinear data points in a multidimensional space.

2.4. Random Forest

We can say that it is a collection of decision tree which uses bagging method. By applying an average model technique, bagging is utilized to increase the model's stability and accuracy. Each tree is made up of many random vectors that can be used to vote for the best class to predict. The addition of randomization to the model stops it from overfitting, resulting in a more accurate classification analysis conclusion.[8]

2.5. K Nèarest Neighbours

The K-Nearest Neighbors strategy is a distribution-free approach for pattern recognition classification and regression. In both cases, the input is the k nearest practise instances in the feature space.When it is used for categorization, the analysis performed on the data determines class membership. A piece of property is classified by a majority vote of its immediate neighbours.[9] The object is assigned to the most often occurring class among its k nearest neighbours, where k is a positive number that is typically small. If k equals 1, the item is assigned to the class of its single nearest neighbour. If the K-NN is employed as a regression model, the outputs of the KNN are the object's attribute values. This is the average of the k closest neighbours.

2.6. Naive Bayes

It is a set of simple classifiers based upon implementing the Bayes hypothesis to features that must have crucial (naive) independence. One of the most fundamental Bayesian network models, it has been the subject of extensive research since the 1960s. In the early 1960s, it was originally introduced to the text retrieval community (but not under that name). It can also be utilised in automatic medical diagnosis. Naive Bayes classifiers demand a linear association between the frequency of parameters and the number of factors in a training challenge. [10]

2.7. C4.5

C4.5 is based on the entropy assessment of the Information Gain Ratio (IG). The IG report is used to select a test attribute from each node in the tree. The test task is characterized by the highest percentage of information gain ratio for the current node.[11]

2.8. MLP

McCulloch and Pitts established the Artificial Neural Network (ANN) in 1943. The ANN is a complex computer model biologically based nervous systems. It is composed of numerous basic components called neurons that are organised into input, hidden, and output layers. Each neuron in the network has its own set of input values, a barrier, and an activation function. Changing consequences connect neurons in different layers according to a learning process, resulting in a particular desired output from a specific input. Neurons are frequently combined in the most straightforward artificial neural network to allow data to flow from input neurons to hidden neurons and work. A multilayer perceptron (MLP) is indeed a form of a convolutional neural network composed of many layers of neurons that are entirely coupled.[12] MLP networks can approximate and satisfy universal approximation for any form of constrained piece - wise linear combination with sufficient training and hidden layer numbers. When used in conjunction with an optimization technique such as gradient descent, the MLP network employs backpropagation (BP).This method of supervised learning is commonly recognised as the most effective way to train neural networks. The BP technique identifies errors by estimating the differences among expected and calculated values. After that, the error is transmitted back through the network, revising the weights and getting the best outcomes. The technique is monitored until the difference reaches a pre-set threshold. The neural network procedure has gained significant the most consideration as an efficient and accurate approach that produces results considered superior to those obtained using conventional techniques due to its autonomy from whatever prior knowledge of the nature of interactions among inputs and output.[13]

2.9. Gradient Boosting

The learning mechanisms of the Gradient Boosting Machines (GBM) adapt the new models in a sequence to allow a more accurate estimation of the response variables. The main idea of this algorithm is to create new base learners that are maximally correlated with the negative gradient of the set loss function. The loss functions used can be any; However, to give you an idea, if the error function is the traditional squared error loss, the learning approach leads to a gradual adjustment of the error. In general, the researcher has complete control over the loss function, with a variety of previously derived loss functions and the ability to develop activity-specific losses. Thanks to their great versatility, GBMs can be adapted to any data-driven activity. On the other hand, it leaves a lot of room for the model designer, so choosing the best loss function is a matter of trial and error.[14]

3. LITERATURE REVIEW

Rahman et al. [15] researched to determine the usefulness of numerous machine learning techniques have been successful in lowering the primary prediction costs associated with the identification of chronic liver illnesses.Six distinct algorithms were employed in this study: decision tree, support vector, bayesian networks, logistic regression, and random forest. The accuracy, precision, recall, f-1 score, and specificity of numerous categorization algorithms were evaluated. The LR shows highest accuracy of 75%, then RF 74%, DT 69%, SVM 64%, KNN 62%, and least accuracy was shown by NB 53%., The research revealed that the LR had the best accuracy.

Rabbi et al. [4] For classifying the Indian Liver Patient Dataset, we used four distinct types of MLA: Logistic Regression, Decision Tree, Random Forest, and Extra Trees (ILPD). Pearson Correlation Coefficient based feature selection (PCC-FS) is applied to eliminate irrelevant features from the dataset. Along with it to increase the predictive performance AdaBoost one of the boosting algorithms was used. The analysis is evaluated in respect of accuracy, ROC, F-1 score, precision, & recall.After comparing experimental results, we have found that boosting on ET provides the highest accuracy of 92.19%.

Cao et al. [16] proposed an early test method using the clinical laboratory data set. GBDT i.e., Gradient boosting trees, was used to select essential features, followed by training and testing. Two type of Classification algorithm was used one is Support Vector Machine and other GBDT. The Kappa index approaches near perfection, and the accuracy exceeds 90%, according to the findings.

Das et al.[17]. MLP and decision tree classifiers were used to analyse CT images of hepatocellular and metastatic carcinoma. Fourier analysis was employed to extract important features from the LBP histogram. Finally, the decision tree classifier achieved 95.02 percent accuracy out of the two machine learning classifiers.

Meng et al. [18] examined MRI images of liver cancer. At first, Histogram based feature has been used for the extraction of feature, then for the prediction SVM was used. This technique predicted primitive stage liver cancer with an accuracy of 86.67 percent and benign type tumours with an accuracy of 80 percent.

Naeem et al. [19] The researchers analysed a fused two-dimensional dataset of computed tomography and magnetic resonance images in benign hepatocellular adenoma and hemangioma cysts, as well as malignant hepatocellular carcinoma and hepatoblastoma liver cancers. The received dataset was pre-processed, and Gabor filters were employed to minimise noise.

Ten significant hybrid features were identified using the likelihood of error plus average correlation feature selection technique. Then tenfold cross-validation procedure was used procedure to deploy this improved hybrid feature dataset to ML classification algorithm that is Support Vector Machine, J48, multilayer perceptron (MLP), and random forest (RF). MLP had 95.78 percent MRI accuracy and a 97.44 percent CT accuracy overall. Out of all four, MLP has achieved 99 percent accuracy.

Krishna et al. [20] CT images were preferred over the more often utilised Positron - Emission and Magnetic Resonance because they produce higher-quality images and are less expensive. For the feature extraction SFTA, that is, Segmentation based Fractal Texture Analysis was used. Then for the classification, Naive Bayes and SVM were used. Out of the two classifiers, SVM performed better with an accuracy of 92.5%

Li et al. [21] proposed an automated process using CNN to section lesions from CT images. Then it was compared with AdaBoost, Random Forest, and support vector machine. Handcrafted characteristics incorporating mean, variance, and contextual variables were used to train these classifiers with the thirty-portal phase enhanced CT images were examined experimentally using leave just one testing data. The average Dice Similarity Coefficient (DSC), precision, and recall achieved 80.06% ± 1.63%, 82.67% ± 1.43%, and 84.34% ± 1.61%, respectively. By analysing the output, it is observed that CNN has performed better.

Rajesh et al. [22] examined HCC liver cancer using KNN, Naïve Bayes, DT, RF, and SVM. They proposed a model to predict the HCC. 80.64% accuracy was achieved by RF without any cross-validation accuracy whereas all other classifiers were employed using 10-fold cross validation.

Das et al. [23] The Pictures of a liver were analysed primarily for the purpose of differentiating cancer lesions and predicting the various types of liver disease, which include hemangioma, hepatocellular carcinoma, and metastatic carcinoma. To segment the liver, we used part marker-controlled floodplain fragmentation and a Gaussian mixture model to differentiate cancer-affected regions. Finally, 99.38 percent accuracy was reached for classification using DNN.

Kalsoom et al. [24]proposed an combination of unsupervised machine learning technique and supervised mechanism for properly segmenting tumours in liver. The features like LBP and HOG have been extracted, and classification is done using KNN. The overall accuracy of 97% is achieved. As compared to SVM and Ensemble, which have shown the accuracy of 85% and 49%, respectively, KNN has performed better.

Jacob et al. [25] compared four algorithms SVM, Logistic Regression, KNN, and ANN. Performance was calculated using different evaluation metrics. The ANN fared the best, with a precision of 98 percent.

Saritha et al. [26]proposed a new algorithm called separation of points by plane, it uses a technique of maths to separate N number of data points by a certain number of hyperplanes. The data set used was the Real Data Set of LFT, taken by the "MEDCIS PathLabs India Private Ltd." Hyderabad. The proposed method can predict the disease with 85.1% accuracy with training and testing time of 1 sec, respectively.

Roslina et al. [27]The author used the carrier vector machine (SVM) and the wrapper method to predict the prognosis of hepatitis disease. Prior to the classification process, they used packaging methods to remove the noise characteristics. First, SVM selects features to achieve better accuracy. Feature selection is implemented to reduce noise or irrelevant data. Through the experimental results, they saw an increased accuracy rate of the cost of clinical laboratory tests with minimal run time. He achieved the goal by combining wrapper method and SVM techniques Initially the accuracy was 72.73%, while after feature selection method the increase accuracy was 74.55%

4. RESULT AND DISCUSSIȮN

Numerous methods and algorithms of diagnosing liver cancer are evaluated and compared to a variety of observed data. The TABLE 1 shows how different studies utilised different feature extraction approaches and classifiers. From the analysis we can observed that Image Dataset shows better accuracy as compared to the Numerical Algorithms based on CT scan pictures are by far the most efficient and provide up to 99 percent accuracy.

Table.1: Comparison and summary report

Sr.No.	Paper	Dataset	Feature Extraction	Classifier	Accuracy
1	[15]	UCI Machine Learning Repository	-	LR	75%
2	[4]	Indian Liver Patient Dataset (ILPD).	Pearson Correlation Coefficient	ET	92.19%
3	[16]	clinical laboratory data set	Gradient boosting decision trees	SVM	90%
4	[17]	CT images of hepatocellular and metastatic cancer	LBP histogram Fourier	DT	95.02%
5	[18]	MRI Images	Histogram	SVM	86.67%
6	[19]	Fused 2D dataset of CT and MRI	error probability plus average correlation	MLP	99%
7	[20]	CT Images	Segmentation based Fractal Texture Analysis	Naïve Bayes	92.5%
8	[22]	UCI machine learning repository named as HCC S	-	RF	80.64%
9	[23]	CT images	Gray level co-occurrence matrix (GLCM)	DNN	99.38%
10	[24]	3DIRCADb Dataset.	LBP and HOG feature	KNN	97%
11	[25]	Indian Liver Patient Dataset (ILPD)	-	ANN	92.8%
12	[27]	UCI Machine Learning Repository	Wrapper Method	libSVM	74.55%

The grey gradient co-occurrence matrix (GLCM) is an approach for extracting features. has shown more accuracy as compared to Segmentation based Fractal Texture Analysis on CT scan images, first has shown accuracy of 99.38% former has shown 92.5% accuracy. Fused image of CT scan and MRI with error probability plus average correlation feature extraction technique has shown 99% accuracy result.

5. CONCLUSION

The failure to detect cancer at an advanced stage is the cause of death from liver cancer. As a result, early prediction is essential, that can be accomplished with the use of computerization in cancer diagnosis. Early identification of cancer is achievable with different machine learning techniques, which could save the lives of many patients. This study summarises previously published works that used a different machine learning approach to detect and diagnose liver disease.Different algorithms perform differently in different situations, but dataset and feature selection are also essential in improving prediction outcomes. Additionally, the paper contains an assessment of a range of machine learning strategies in use by multiple writers, with each methodology providing both positive and negative results depending upon that datasets and features used, among other aspects. With this investigation, we discovered that adopting a new combination or hybrid machine learning method may improve accuracy and performance, and that in the future, we can investigate more factors to improve performance over the current technique.

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