www.ijarp.com ISSN 2456-9992 Page: 01-19

International Journal Advanced Research Publications

Research Article

Volume: 02

Issue: 02

AUTOMATED LIVER TUMOR DETECTION AND PROGNOSIS USING INTEGRATED AI TECHNIQUES

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Article Received: 10 January 2026, Article Revised: 30 January 2026, Published on: 18 February 2026

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DOI: https://doi-doi.org/101555/ijarp.7413

ABSTRACT

In human body liver is one of the most important largest organ which is mainly used for controls the blood flow, filters the blood, maintains the red blood cells, and maintains the digestion system. Liver lesion is one of the most common and effective deadly diseases which affects the liver with abnormal tissue growths. Although liver cancer which spreads the deadly tissues in the blood and lymphatic systems. Liver tumor happens when the abnormal growths of the deadly cells will affects the liver, and this kind of diseases will stops the liver work flow and spread the rest to the body. It can have several types of symptoms for various stages. It often diagnosis the combination of research in imaging and blood tests. In medical field imaging which mainly diagnosis by MRI or PET scan image. Our proposed method which explores advanced imaging modalities and deep learning techniques for the early detection and appropriate treatment or therapy of the liver cancer.

KEYWORDS: Deep learning, CNN, LENet, LECNN, CAT Boosting, YOLO V8, Faster R-CNN, U-Net.

INTRODUCTION

Liver is one of the major part of the body which maintains the red blood cells and digestion of the liver. The liver lesion which refers abnormal growth of deadly cells in the liver tissues. It is broadly classified in to two different types of categories they are benign (cancerous) and malignant (non-cancerous). It consists of several symptoms with various stages in Table 1 were the liver has been affected. Moreover, the benign lesions which is mainly consist of hormonal changes and another type of the malignant lesions which is mainly consist of deadly changes like cirrhosis or fatty liver diseases. In our proposed research medical imaging which plays the major role in process of scanning images for early diagnosis and treatment or therapy for the liver. Our previous research studies were performed by the action of ultrasound and CT scan of the affected region of the liver. Similarly it might be have some challenges and limitations in previous research studies. The Figure 1 which explains about the liver region affected by the cirrhosis.

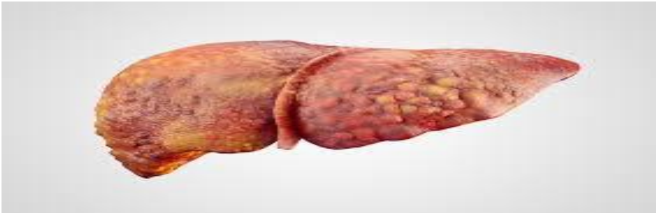

Figure 1 Liver cancer affected region of Cirrhosis.

Our proposed research which explores advanced imaging of MRI scan and deep learning techniques for the early detection and appropriate treatment of liver cancer. Moreover, the datasets have been collected by kaggle website and it can split the data in to training, validation and finally

Table ***2*** shows it can be completely tested by the valid dataset. Our previous research studies will mainly having challenges in varied appearances, and difficult to identify the differences in tumors. This advanced research will mainly encloses the difficulties and challenges of our previous research studies. In this proposed research study Figure 2 Shows that the part of the liver will be affected by various stages of liver lesions. Since, the proposed research study will efficiently performing with the radiologists for to overcome the liver lesion deadly final stages.

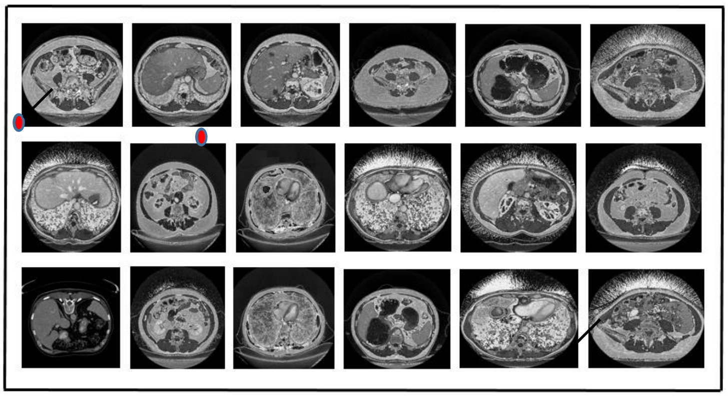

Figure 2 Various stages of affected liver lesions

Table 1 Representation for identifying the characteristics in liver lesions.

SI.No.	Characteristics	Benign tumors	Primary level of malignant tumor	Metastatic liver cancer
1.	Samples	Hemangioma, FNH, Hepatocellular adenoma	HCC, Cholangiocarcinoma	Cancers from colon
2.	Cell origin	Non- cancerous liver cells	Hepatocytes or bile ducts	Cancer cells from other organs spread to the liver
3.	Growth pattern	Slow-growing, non-invasive	Rapid growth, invasive	Depends on primary cancer
4.	Stages	Not staged (non-cancerous)	Staged I-IV (TNM staging system)	Staged based on primary cancer and spread
5.	Primary symptoms	Often asymptomatic	Fatigue, abdominal pain, nausea	Fatigue, weight loss, mild liver discomfort
6.	Advanced symptoms	Rare discomfort due to tumor size	Jaundice, weight loss, abdominal swelling (ascites)	Jaundice, severe abdominal swelling, confusion
7.	Risk Factors	Hormonal imbalances, Genetic predisposition	Cirrhosis, Hepatitis B/C, Alcohol abuse, Obesity	Primary cancer type (e.g., Colon, breast)
8.	Diagnosis	Ultrasound, (CT/MRI)	Alpha-fetoprotein (AFP), biopsy, imaging studies	Imaging studies(CT/MRI), biopsy
9.	Treatment Options	Monitoring, surgery (if symptomatic)	Surgery, liver transplant, targeted therapy.	Depends on primary cancer

Table 2 Representation of overall pre-processing steps.

SI.No.	Work Flow	Explanation
1.	Preprocessing	Noise Reduction, Contrast enhancement, Histogram equalization, Intensity variation,

2.	Segmentation	Deep lab V3
3.	Feature Extraction	CNN, DenseNet, VGG17
4.	Classification	CNN, Faster R-CNN, FCN

MATERIALS & METHODS

In this research study, our main target is to explore advanced image processing techniques and effective algorithms for the clinical purpose. About the datasets depository information various liver lesion images of 20,000 images has been collected and CSV file also be collected for the liver lesion clinical research. In our medical research the datasets has been split into various processes for the early detection and treatment of liver cancer. The advanced artificial intelligence explores deep learning and ensemble techniques for the early identification of liver lesion difference and efficient treatment like therapy or surgery. The process of liver lesion samples which can be split as 10,000 images for training, 5,000 images for validation and 5,000 images for testing can be implemented. Using this requirements we are implementing our proposed research mainly on object detection, detection transformer, classifying the image difference, segmenting the samples in to different parts for the performance metrics. This research will explores the advanced algorithms for the liver lesion detection such as CNN, YOLO V8, Faster R-CNN, residual network, U Net and multi-level feature pyramid network.

LITERATURE REVIEW

SI.No.	Author Name & Year	Title	Methods / Techniques	Algorithms used	Merits	Demerits
1.	Shengillog & 2025	A comprehensive meta-analysis of stem cell therapy for liver failure	PRISMA, Statistical analysis, Cochrane risk of bias	Kaplan-Meier Curve	Mesenchymal stem cell therapy improving clinical outcomes	Limited small samples
2.	Zi-Chen Yu & 2025	Clinical characteristics, Patterns, of Recurrence	Kalpan-meier survival curves	Recurrence free survival	DPHCC improves overall survival rates	Impacting the perceived efficacy of adjuvant treatment
3.	Jing Zhou & 2025	Magnetic resonance imaging radiomics based on AI	AUC and RFS	Linear regression and Light Gradient boosting	Enhancing diagnostic accuracy	Challenging in analytic tools

				machine		
4.	Caiyyun Yang & 2024	Surveillance and management of HCC after treatment of hepatitis C	RNN, SVR and baseline techniques	RNN and aMAP	Reducing unnecessary healthcare costs	Lack of universal applicability and inadequate monitoring
5.	Chun-Ying & 2024	Clinical guidelines for early HCC treatment options	Radiofrequency ablation and surgical resection	Adaptable treatment	Reliable and transparent	Increased risk of RFA procedures

IMPLEMENTATION

Our proposed research has been implemented in the python3 by using the Google Co-lab. In this proposed research we implementing the process of segmentation, feature extraction and classification process using advanced deep learning algorithms. Our proposed methodology has been used for the early detection of liver cancer and the appropriate treatment like therapy without using surgery or biopsy. In our previous research studies they can implemented more variety of algorithm techniques but they have some limitations in that research. Due to lack of annotation data samples and challenging process of liver cancer for the early identification.

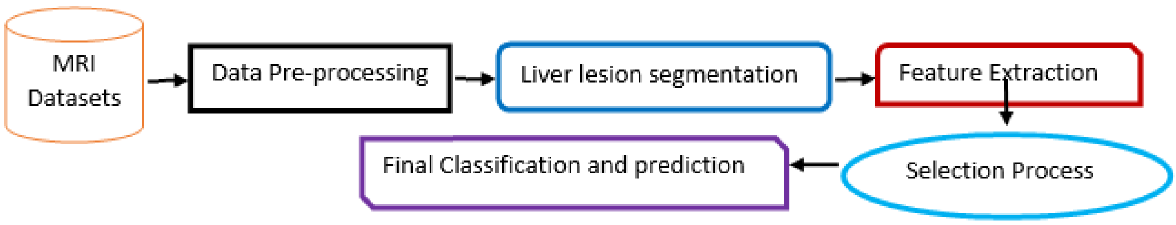

Figure 3 Enhanced performance of liver lesion identification

Using this

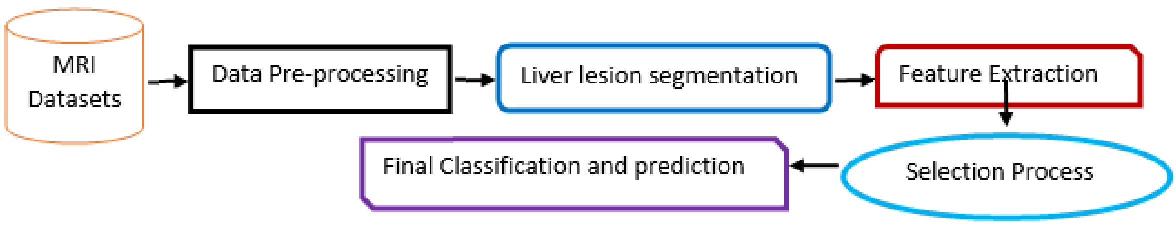

Figure 3 it shows that the architecture is defined by CAD and advanced AI algorithms. In this proposed research we implemented ensemble methods for the efficient diagnosis of the early liver cancer detection. Since, the proposed architecture use MRI scan images for the

accuracy of the identification of the liver cancer. The proposed architecture can be used in the object detection, image classification, segmentation, gray scale conversion, multitask learning and the segmentation process. The advanced algorithms of CNN can be used for the proposed research with the backbone of Yolo v8, faster R-CNN, ResNet, UNet++ and the multitask learning for the fine tuning. Our proposed research which explores the advanced methods and techniques for the early detection and treatment for the liver lesion. In liver lesion detection the appearance and anatomy of the patient history has been difficult to identify with accuracy. This overall proposed research analysis will explore the radiologist's expertise by using the advanced techniques and accuracy.

DEEP LEARNING AND ENSEMBLE TECHNIQUES

The deep learning is an advanced algorithm which enhance some ensemble techniques of boosting algorithms. Our proposed method is mainly used to explore CAT boosting algorithm for the fine tuning and it can be used to generate the results for the early detection of the liver cancer. In this proposed research the

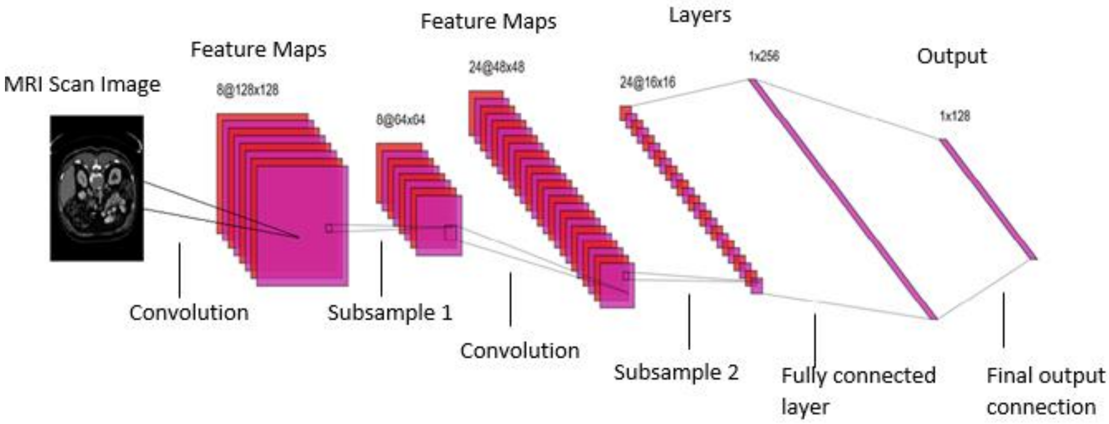

Figure **4** ensemble techniques is used to enhance the overall performance of the classification and prediction by reducing the overfitting and enhancing the accuracy. Deep learning algorithm is used to detect and segment the affected region of the liver by using advanced algorithms and ensemble techniques. Liver lesion having various symptoms on stage wise variety diseases. The advanced research of LECNN network can be used to extracting more advanced features for the early detection and treatment of the liver cancer. It is the process of calculating the accuracy for the liver lesion using the valuable datasets and the advanced technologies for this medical research. In our proposed research study deep learning enhanced algorithms can be used by the formation of SSD optimizer. Deep learning is the advanced algorithm technique in the worldwide. Our proposed research used deep learning backbone of advanced algorithms. This proposed algorithm and techniques will be useful for the identification of the liver lesion.

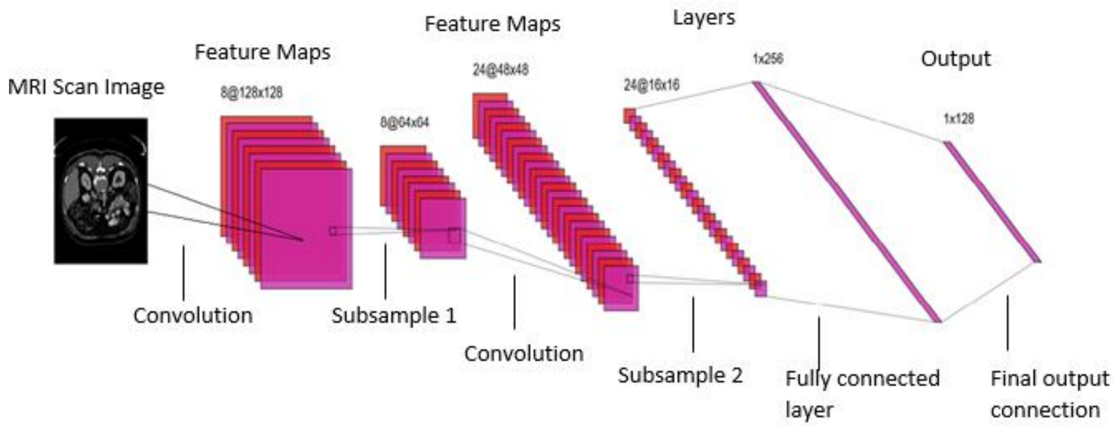

Figure 4 Architecture of Advanced LECNN Network

MODEL PARAMETRIC OPTIMIZATION

The SSD optimizer is an advanced tool which is mainly used in the research for detecting large datasets. Single shot Multi Box Detector (SSD) is a famous object detecting tool for the identification of the abnormal region of the affected liver. SSD optimizer is mainly used in our proposed research for the accuracy and detecting the affected regions with more effective. The model which can be explored the batch size 68 with the learning rate of 0.0008 for the effective early identification of the liver cancer. Our advanced proposed research has been effectively performed for the pre trained model around the values of 70, 130 and 300 epochs, for the advanced research of AI. This advanced SSD optimizer is used in the gradient descent for smoothing the image classification.

ALGORITHMS FOR ADVANCED PROPOSED RESEARCH

Step 1: Given the MRI image of input data and labelled image by $\{(X_i, Y_i)\}$ where equated the input image as X_i and the labelled image as Y_i. This collected data is used for the feature category F_c with the appropriate data.

Step 2: Using the Normalization by the given pixel values are,

$$XY' = \frac{XY - \min(X)}{\max(X) - \min(X)} \quad \dots\dots\dots\dots (1)$$

Step 3: Using the Augmentation by the given pixel values are, this given equation which explains about the rotation, flipping and image cropping.

$$XYaug = f(X)aug\,(XY') \quad \dots\dots\dots\dots (2)$$

Step 4: Using the CAT boosting algorithm for the effective planning categorical data has been equated by the,

$C = C + B \quad XY \quad \ldots\ldots\ldots\ldots(3)$

Step 5: This advanced LECNN network which has been extracted by the different features,

$LECNN = \{(C1, P1 \quad C2, P2) + (LC1 + LC2)\} \quad \ldots\ldots\ldots\ldots(4)$

- Where, the equations of C1 and C2 is the number of convolution layers with the activation function.

$hw = \max(0,1, W \times XY + a) \quad \ldots\ldots\ldots\ldots(5)$

- P1, P2 are the layers which has been pooled by reducing the dimensions.

$Xw = \max X$

- LC1 and LC2 are the layers which has been used for the final full connected networks.

$F = LC(LCNN(Xavg)) \quad \ldots\ldots\ldots\ldots(6)$

Step 6: Classification model using Cat Boosting by defining the boosting on F and trained category various features on C.

$XY = Cf = F + C'f \quad \ldots\ldots\ldots\ldots(7)$

Step 7: Using the decision tree algorithm by the form of gradient boosting where the L is the

$L = -\Sigma \log(xy) + (1 + y)\log(1 - Y) \quad \ldots\ldots\ldots\ldots(8)$

Step 8: Using weight boosting algorithm for the Cat Boosting can be considered as,

$W = wt = wt + 1.wt - 1\ (1 - \eta).(1 + \sigma wt - 1) \quad \ldots\ldots\ldots\ldots(9)$

Step 9: Using the algorithm of backpropagation weights for CNN,

$Wt(t+1) = 1 + (W(t) - \alpha\left(1 + \frac{\delta L}{\delta W}\right) \quad \ldots\ldots\ldots\ldots(10)$

Where the equation 10 αL is the learning rate of this algorithm.

Although the boosting algorithm is mainly used for the fine tuning that hyper parameters for the Bayesian optimization using cross validation for preventing overfitting.

Step 10: Finally the last process combining both CNN and boosting algorithms for the calculation of prediction using a fusion weight.

$Y = CNN + (1 + X) - (1 - Y).Y \quad \ldots\ldots\ldots\ldots \quad (11)$

Where fusion of the weight can be optimized in the weight of the search. The final classification can be used for the decision making by this equation 12.

$XY = \arg(min + \max(\mathrm{X} + \mathrm{Y})) \quad \ldots\ldots\ldots\ldots(12)$

INVESTIGATION OF LIVER LESION STUDIES

In the Figure 5 shows that the process of liver lesion detection presents the different stages of tumors with a significant challenges data. The process of comparative values can be visualized for the various mean levels. The proposed research will analyse the platelets in stage wise for the early detection of low blood cells. The different stages of proposed platelets values can be diagnosed by multiple datasets.

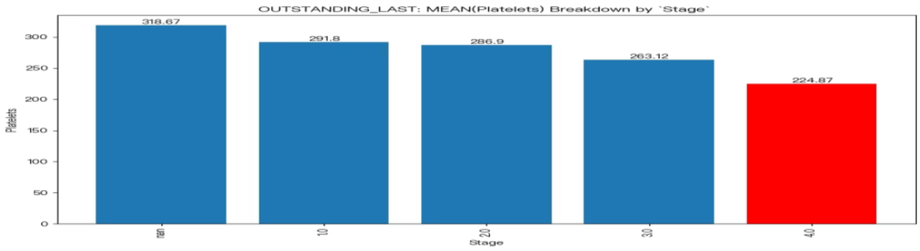

Figure 5 Different stages of Platelets

In our proposed research study the liver cancer has been detected by various frequency rate of distribution. The Figure 6 shows about the incident rate of the frequency. The liver cancer research which is mainly focus to identify the low platelets for the early treatment. This fig 5. Helps to identify the rate of frequency on different countries were affected by low platelets.

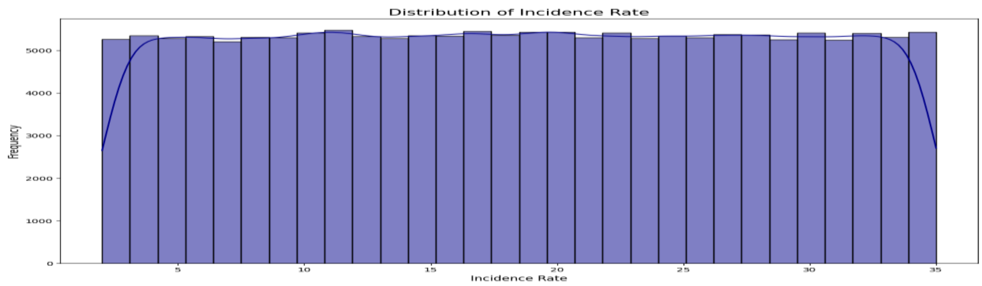

Figure 6 Incident rate of low platelets

COMPARATIVE STUDIES OF LIVER FUNCTION TEST

In Figure 7 this proposed research liver cancer various function test has been generated by using gender. This liver test function is mainly explores for the identification of different patient anatomy details and the difference between the affected people and the non-affected people. The comparative studies which can be used by the list of various genders with type of testing and liver function. The various affected parts of liver cancer can be identified using patients testing details like blood tests, tumor biomarkers and biopsies.

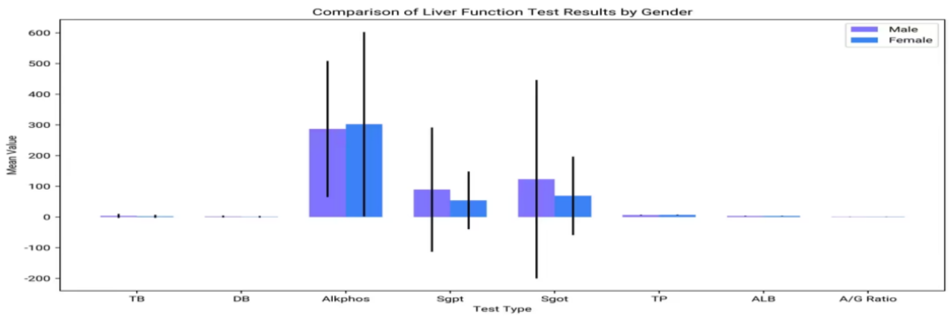

Figure 7 Comparison of Liver Function Test

STATISTICAL ANALYSIS OF LIVER LESIONS

In our medical research analysis Figure 8 shows 585 records, 11 attributes and it offers more information for the liver lesion detection using different parameters. Moreover it provides the detailed information of the patient and various types of diseases. This datasets mainly highlights the various types of liver cancer disease and it is also used for the critical analysis for the early detection and patient outcomes.

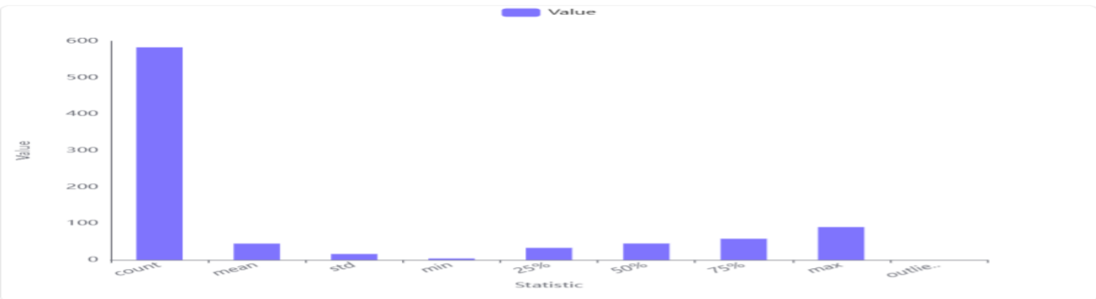

Figure 8 Statistical Analysis of Liver Cancer.

In Figure 9 it shows that the various functions of liver test can be statistically analysed using various patient details. It can be used for the analysis of various range values. This result will be useful for the early diagnosis of the liver function changes. The different statistical analysis of liver cancer can be used to explore the various functions of liver cancer. The liver cancer will affects various parts of the body and the affected region can be detected using the multiple tests for more accuracy result of the early detection of liver cancer. These test values can be used to identify the various stages and symptoms of liver cancer. This liver function will mainly use to detect the deadly cells of the liver tissues. In this proposed research we compared all these tests with the previous studies and applied the effective proposed research testing for the diagnosis of early liver cancer.

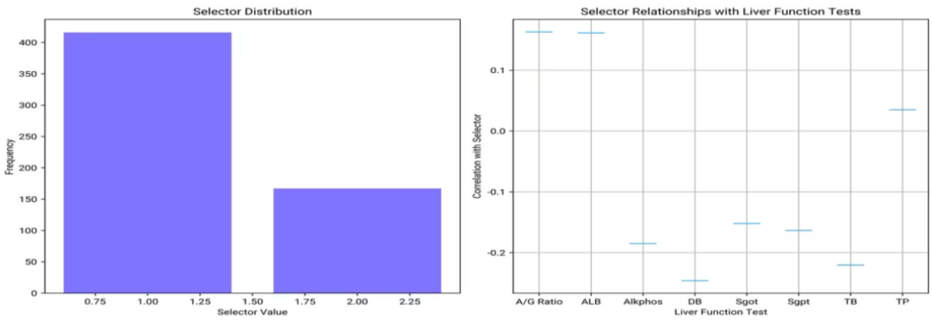

Figure 9 Test Values of Liver Cancer.

In the Figure 10 shows that the various places of death rates affected by alcohol. It can be calculated using the various levels death rates by splitting as low, moderate and high. The liver which can be affected by most kind of cirrhosis and analysed by these results. The impact of mortality can be raised by the reason of uncontrollable alcohol consumed. The cirrhosis and fibrosis is the scarring and deadly diseases.

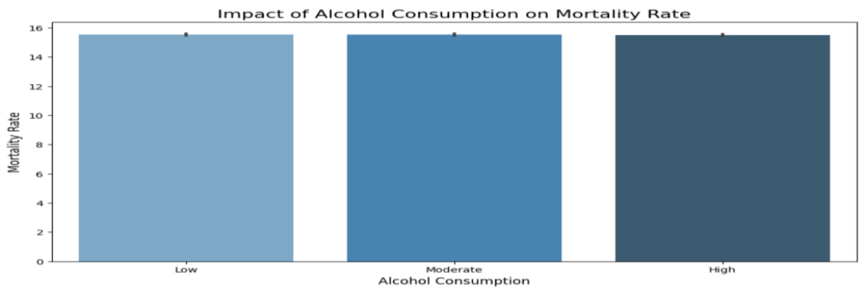

Figure 10 Impact of various mortality rates.

In the Figure shows that the Correlation heat map can be calculated by the various features in the liver cancer. This heat map shows that the population, incidence rate, mortality rate, age, survival rate and cost of the liver cancer treatment. The correlation map which is mainly used for the testing and calculating tumors and with different patient details.

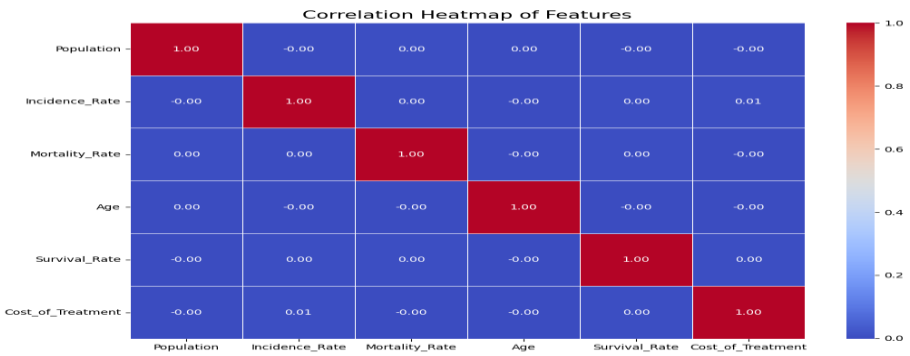

Figure 11 Correlation heat map of various features.

In the Figure shows that the prediction of liver cancer can be calculated by the various levels using various deadly cases and it shows whether the liver cancer is affected or not by using various counts. Most type of the liver cancer cases can be affected by the alcohol consumption.

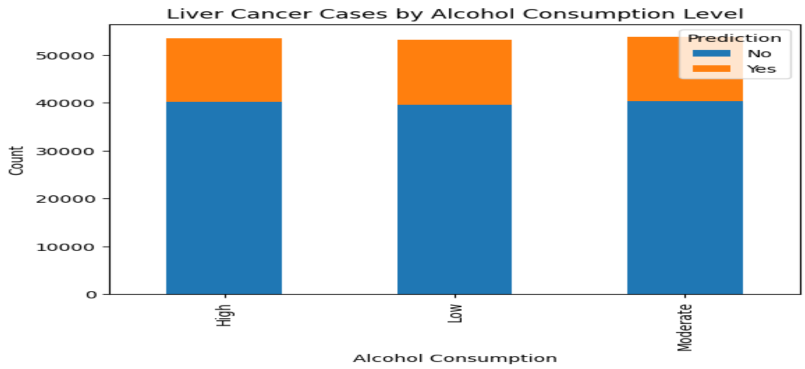

Figure 12 Liver cancer prediction level.

In the Figure shows that the liver cancer can be affected by various features by various age and genders. This process is used for the liver cancer detection of classification and prediction. The correlation map which is mainly used for the prediction of the liver cancer.

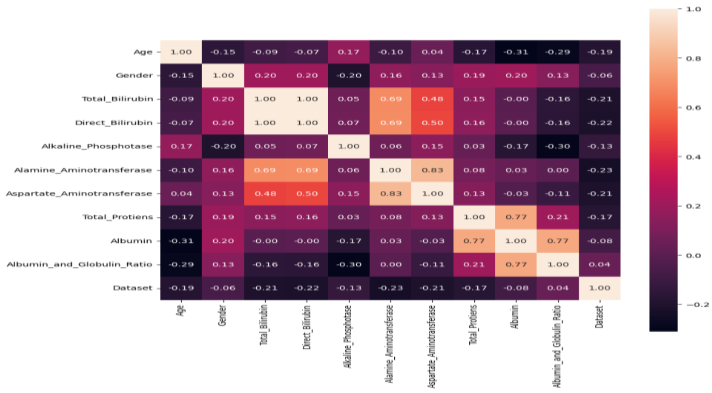

Figure 13 Liver cancer correlated heat map of various features

CLINICAL OBSERVATIONS

In Figure it shows that the clinical research for the liver lesion can be used for the analysis of the various outcomes. It is used to specify the ranges of outcomes. The overall outcome of the liver cancer count can be used for the distribution of list of lesion status.

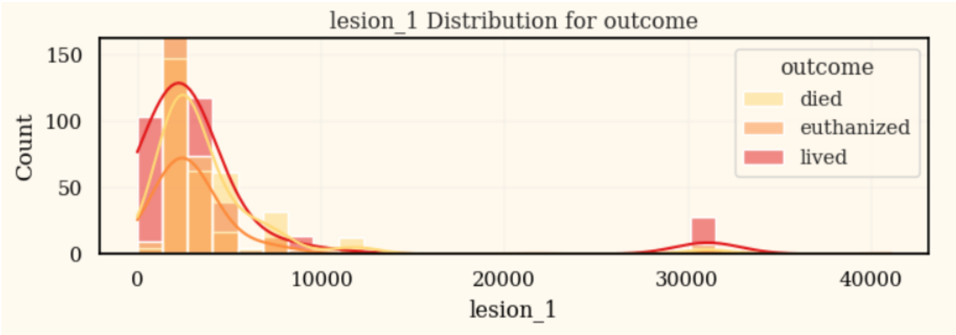

Figure 14 Liver lesion analysis of overall outcomes.

EXPERIMENTAL ANALYSIS OF PROPOSED WITH VARIOUS METHODS

The analysis of proposed method and various methods can be identified using the updated values of the proposed and various methods. This analysis which is mainly used to detect the liver cancer in early for the appropriate treatments and therapies. In Figure 11 shows that the final proposed results is used to detect the various affected liver cancer region for the early detection and patient outcomes.

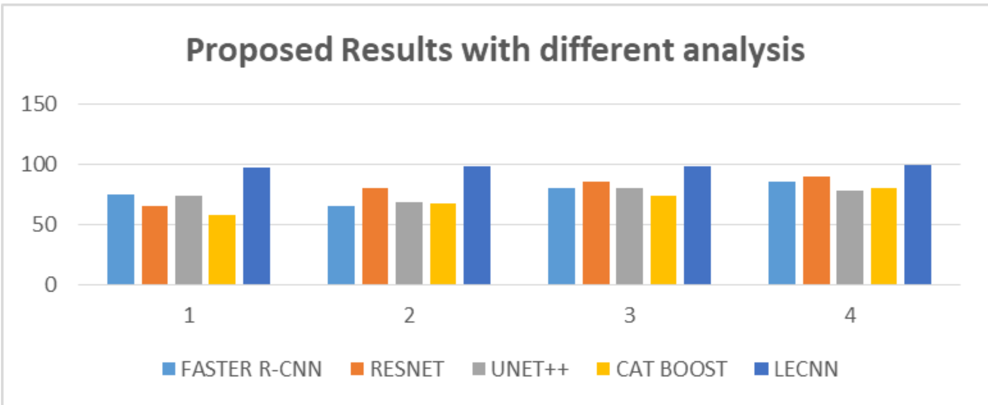

Figure 11 Liver cancer Proposed Result Analysis.

PERFORMANCE METRICS

Our proposed research study performs various metrics which has been evaluated by the following techniques. The overall list of performance metrics are accuracy, precision, F1 score, recall and a pertinent performance can be evaluated by bar graph using various metrics. In Figure it shows that the final analysis of the performance metrics using bar chart.

- In our proposed research accuracy can be used by

$$ACC = \frac{TP + TN}{TP + FP + FN + TN}$$

- Another process of precision can be used by

$$\text{Precise} = \frac{TP}{TP + FP}$$

- Recall can be used for the detecting affected cases by

$$\text{Recall} = \frac{TP}{TP + FN}$$

- F1-score is used for the balancing the mean value of both metrics.

$$\frac{\text{Precision x Recall}}{\text{Precision + Recall}}$$

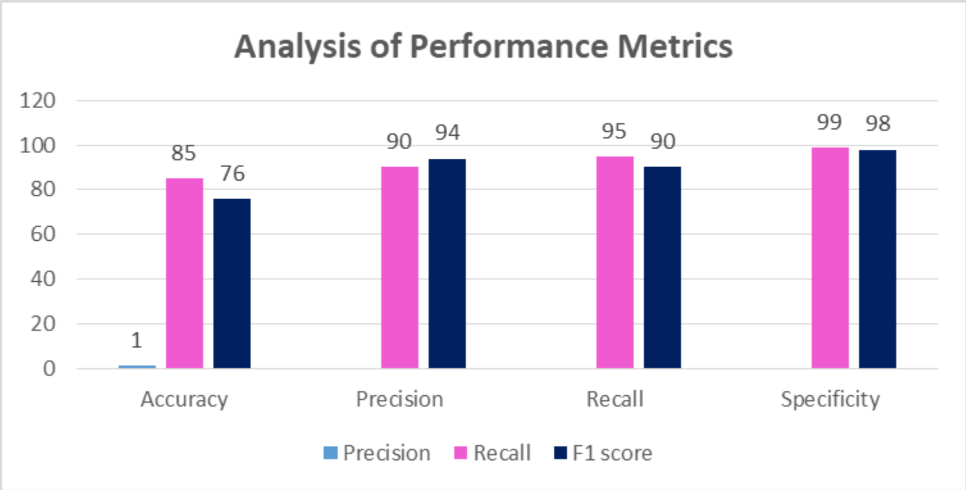

Figure 16 Final results of performance metrics.

RESULTS & DISCUSSION

Our proposed research work used advanced deep learning algorithms and ensemble techniques for the early detection of liver tumor. Our research deeply aims to identify the difference between the cancer and cancerous patients. In our existing study they used more algorithms and techniques but they have some limitations such as lack of overlapping tissues and motion artifacts. Our proposed research specified algorithms are CNN, LENET, CAT boosting for the accuracy detection of the liver cancer. Our proposed research LECNN is used to detect the liver lesion with early and accuracy. It mainly aims to avoid the treatments like surgery. Our proposed research suggesting the treatment such as immunotherapy and various therapies by monitoring for the better patient outcome. Finally we discussed about the challenges of the early detection and the problem of different liver lesion stages of appearance. Liver lesion research is the globally affected diseases and it can be cured by the early detection of liver lesion using advanced techniques.

CONCLUSION AND FUTURE SCOPE

Our proposed research concludes that the development of the advanced deep learning and boosting algorithms with ensemble techniques of LECNN for the early detection of liver cancer. This proposed research will achieved the better accuracy for the early detection of liver lesion. In future research the further process can be use the small samples of data with more annotated data by identifying different samples, advanced technologies for the overcome of most affecting worldwide liver lesion diseases. In future research again they have to overcome the different types of research challenges.

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