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A Systematic Analysis of Liver Cancer Detection Using Deep Learning Techniques

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Abstract: A major cause of death around the globe is liver cancer. Liver cancer is the fourth most prevalent cause of cancer-related deaths worldwide and the sixth most often diagnosed malignancy, by the World Health Organization. Recently, it was estimated that there were about 830,180 liver cancer deaths and 905,677 new instances of the disease globally. Several risk factors contribute to the development of liver cancer, including chronic infections with excessive alcohol consumption, non-alcoholic fatty liver disease, hepatitis C or B, and specific genetic conditions. Prevention and early detection are crucial in reducing the burden of liver cancer, and individuals at higher risk should consider regular screening and lifestyle modifications to lower the risk. Treatment options for liver cancer may vary based on the cancer's stage and the individual's overall health. It may also include surgery, radiation therapy, and chemotherapy. Early detection of liver lesions can improve the chances of successful treatment and cure. An imaging method that is frequently utilized, is computed tomography, which can help detect liver lesions, as well as provide additional information about the size, location, and characteristics of the lesion. There are two types of liver cancer: secondary and primary liver cancer. Secondary liver cancer occurs when cancer has spread to the liver from another section of the body. Primary liver cancer, the most typical kind of liver cancer, begins in the liver. We have classified this paper into two categories: deep learning (DL) based techniques and machine learning (ML) based techniques to detect liver cancer. This survey paper focuses on models such as generative adversarial network, LSTM, Deep residual neural network, transfer learning, Random survival forest (RSF), K-Means Clustering, and convolutional neural network (CNN) which include GoogLeNet and U-Net.

Keywords: Liver cancer detection, Liver tumor segmentation, Transfer learning, Deep learning, Histopathological image analysis, Medical image segmentation, and Convolutional Neural Networks.

1. Introduction

Liver is in the right upper abdominal region above the stomach, and beneath the diaphragm [1]. Many malignancies can develop in the liver some of these is a form of cancer called liver cancer, which develops in the cells of the liver. The liver is an important organ in the body that helps filter toxins and waste products from the blood and is important in many situations for metabolic functions [2]. When the cells of liver begin to grow uncontrollably and form a mass also known as tumor, it might indicate the presence of liver cancer also known as primary hepatic cancer, or primary hepatic malignancy [3]. There are two types of liver cancer: primary and secondary liver cancer. Primary liver cancer is also called hepatocellular carcinoma (HCC), the most typical kind of liver cancer, begins in the liver [4]. Primary liver cancers also include cellular carcinoma, hemangiosarcomas, angiosarcomas, bile duct cancer, and hepatoblastoma. Secondary liver cancer, also called metastatic liver cancer, occurs when cancer has spread to the liver from another section of the body [5].

HCC happens in the liver more often than metastatic liver cancer. Globally, there is an increase in the chances of liver cancer. Primary liver cancer is the fourth most common cause of cancer-related deaths. In 2018, it affected more than 0.8 million people and claimed more than 0.7 million lives all around the world. Hepatitis B and C are both viral infections that may result in liver inflammation, which can lead to the development of liver cancer over time. Both hepatitis B and C are more common in certain parts of the world, particularly in Asia and sub-Saharan Africa, and that is why liver cancer rates are also higher in these regions [6]. HCC affects males more frequently than females. Most diagnoses occur in people between the ages of 55 and 65. Cirrhosis brought on by alcohol, hepatitis B, and C is the primary contributor to liver cancer. In addition to hepatitis B and C, other factors can increase the risk of liver cancer, including non-alcoholic fatty liver disease, liver flukes, and exposure to aflatoxin (toxins produced by certain molds), obesity, and diabetes [7].

Blood testing, medical imaging, and tissue biopsies may help to confirm the diagnosis. It is essential to consult with a healthcare professional if it is suspect patient may have liver cancer, common symptoms are pain in the abdominal area, weight loss, jaundice, loss of appetite, nausea, and fatigue [8].

Treatment for liver cancer will rely on several things, such as the cancer type, location and size of the lesions, and the patient's general health. Treatment options may include radiation therapy, surgery, chemotherapy, immunotherapy, and targeted therapy [9]. In some cases, a combination of treatments may be used. To minimize the likelihood of developing liver cancer a person should reduce his exposure to risk factors causing hepatitis B and C. Patient should also limit alcohol consumption along with maintaining a healthy weight and avoid exposure to toxins like aflatoxins. Regular check-ups and screenings may also be suggested for individuals with a great risk of cancer developing in the liver. The term "metastatic cancer," is referred to as cancer that originates in one place of the body before spreading to another, such as the colon, lung, or breast. Some of the methods used to detect primary liver cancer and secondary liver cancer include blood tests, ultrasound, Computed tomography (CT), MRI, PET-CT, and biopsies [10].

Some of the imaging methods used to diagnose HCC include computed tomography, PET-CT, positron emission tomography contrast-enhanced ultrasonography, and magnetic resonance perfusion imaging [11]. Nevertheless, due to its excellent sensitivity and specificity, computed tomography is a recommended imaging modality for the identification and diagnosis of HCC and hepatic metastases. High-resolution 3D images are also produced by multi-slice computed tomography scanners with less radiation exposure [12].

Among the most important imaging techniques used in current medical imaging is computed tomography (CT). A rotating x-ray tube is used in CT to collect several readings from a human body x-ray. X-ray imaging reveals varying degrees of degradation as it travels through tissues with varying densities. Then, computational reconstruction and visualization are used to process these measurements. X-ray dose directly affects CT scan reconstruction quality, with greater doses enabling higher-quality reconstruction. However, too much exposure to X-rays can seriously injure a person's body. As a result, cutting down on X-ray exposure while maintaining the quality of CT images becomes a top priority for CT technology advancement. Nevertheless, interference artifacts, non-uniform noise, and a general degradation in image quality for CT scans will be brought on by the reduction in electromagnetic dosage [13].

To identify a tumor in the liver by using various medical imaging techniques requires highly professional and experienced doctors and radiologists. An extremely high level of expertise is required to identify and outline the area of concern. Only a few health care professionals of the required skillset are available worldwide. Computer aided image processing becomes evident under these circumstances. The main advantage of using computer aided image processing is consistency, high accuracy, and less response time as far as results are concerned. This work presents a survey of state-of-the-art image processing techniques. To the best of our knowledge this is the only survey that incorporates machine learning and deep learning techniques for liver cancer detection.

The remainder of the paper is organized as follows: We have discussed the limitations highlighted during the conduct of this study in Section 4. The Taxonomy is given in Section 5. The Performance matrix is given in Section 6 Discussion, and future work is given in Section 7, and the conclusion is in Section 8.

2. Limitations of Liver Cancer Detection

Liver cancer is one of the most common types of cancer with a high mortality rate. The most common reason for this is the lack of early screening and its diagnosis, metastasis, and tumor heterogeneity [14]. This section summarizes limitations that are highlighted during the conduct of this survey.

In the cases where organs, are present in small sizes and limited to small number of slices, suboptimal classification results can be produced. By incorporating more convolutional layers, the neural network's classification results can be enhanced. Also in some cases where classification is performed only on CT scan images, it can be further enhanced using PET scan classification [15].

Utilizing lesion segmentation in any method may come with certain limitations that can be improved. Following are some of the limitations that should be considered: 1. Lesions are unbroken formations that may show up across multiple slices. Slices near the edges of the lesions were lost because of detection errors. By exploring automatic parameter adjustment strategies, the metrics of the RetinaNet can be maximized. 2. The initial segmentation stage minimizes the number of voxels representing healthy liver. However, false positives are still present in the lesion segmentation and segmentation refining processes. To improve the results and reduce the number of others to cut down on false positives, post-processing techniques could be introduced during segmentation refining. 3. The division supplied by the technique in some slices either slightly enlarges or somewhat reduces the specialist's markings. Contour enhancement techniques can be employed to better fine-tune the segmentation [16].

Another limitation in mostly researches, is the dependence on small sample size that can affect the accuracy of results. So more accurate results can be generated by combining deep features with texture features and having access to a huge dataset [17].

EDCNN (Edge enhancement densely connected Convolutional Neural Network) can produce poor results if it is tested on a dataset with a finite number of observations and with slow training speed. Also EDCNN application can be limited due to this and this can be a major cause of failure of any model based on EDCNN [18].

The lack of some variables, such as genetic data, that might be strongly connected to HCC prognosis is a key limitation to be considered in conducting the research. The final staging mechanism can be considerably more precise by including more factors and subsequently modeling on a larger patient sample. Furthermore, while finding more compact and understandable models that maintain high accuracy, is important. To increase accuracy, it is crucial to include several other factors [19].

In scenarios where one rater from each medical center annotates the datasets, it might create label bias, particularly for segmenting small lesions, which is unclear.

By Incorporating additional quality control measures based on consensus annotations can reduce labeling errors and prove gainful for technical assessment and supervised training. The original rankings were made just considering the Dice result, which represents a large tissue. By identifying the top-performing teams purely based on Dice is ineffective, however, integrating different measures can be more effective. Lack of demographic data and imaging data (such as scanner type) can also be a problem for conducting a research [20].

3. Taxonomy of Liver Cancer Detection Techniques

In this paper, existing liver cancer detection techniques based on DL and ML techniques are classified. The DL techniques discussed are Convolutional neural network, Generative adversarial network, GoogLeNet, U-Net, DRNN, LSTM, and Transfer Learning model. ML techniques discussed are K-Means Clustering and Random survival forest (RSF) models as shown in Figure 1.

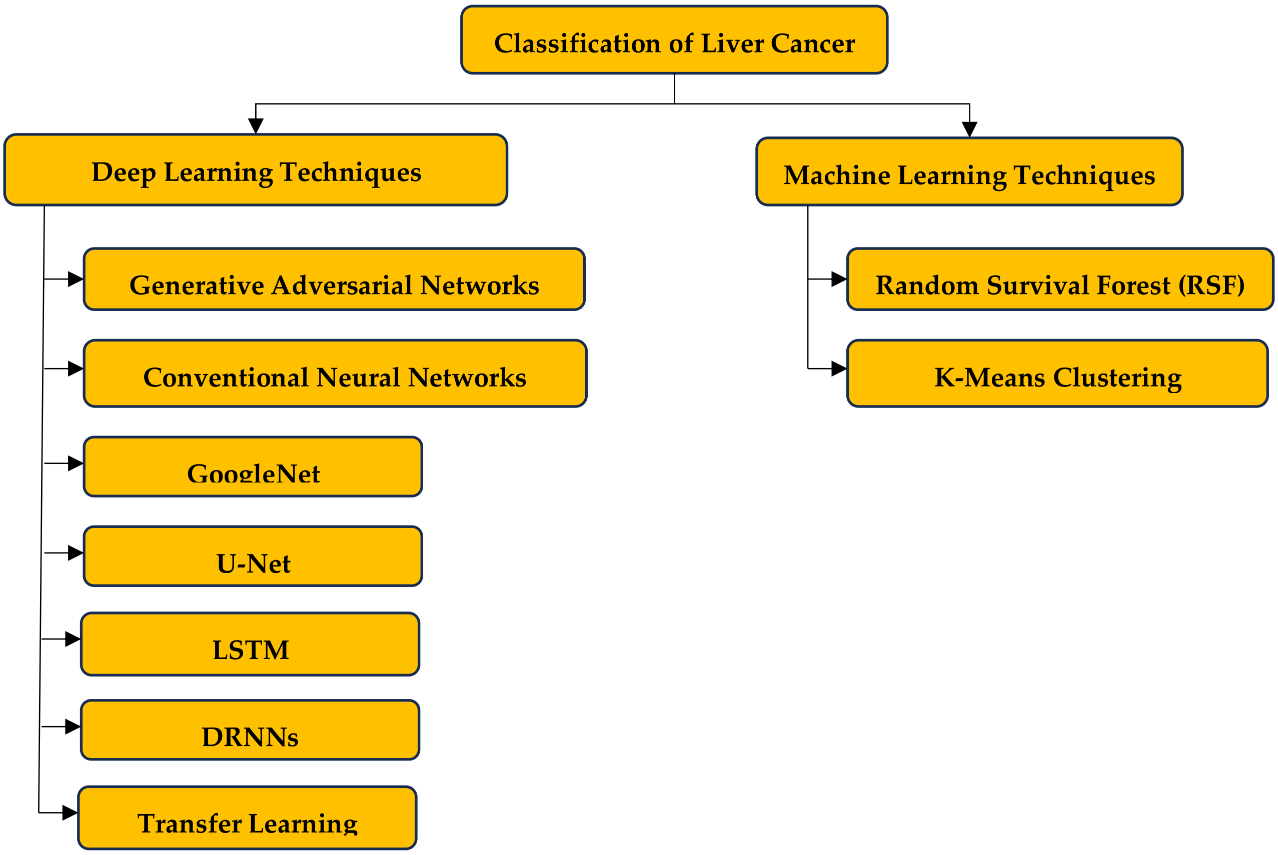

Figure 1. Liver Cancer Detection Using ML & DL Techniques.

3.1 Generative adversarial networks (GAN)

A generative adversarial networks (GANs) is presented in [21]. A generator and a discriminator are the two neural networks that make up the GANs. In GANs, the generator unit generates new data, which is then evaluated by the discriminator unit based on how closely it resembles the training data. Any random number can be used as input by the generator to produce data. For instance, the generator will output an image if we have an issue with an image. The output from the generator and the real information, both are sent to the discriminator. The discriminator manipulates both actual and imagined data. The ground truth data as well as the output from the generator are sent to the discriminator. By returning a value between 0 and 1, which indicates the likelihood of both authentic and fake data, The discriminator tampers with created and real data.

A multi-level GAN to conduct CT scan enhancement is developed in [22]. The photos are altered in three different scales to enhance the output's spectral resolution and spatial. The proposed technique's performance is analyzed using both qualitative and quantitative methods using the Ircadb, LiTS, and Sliver07 datasets, which are all freely accessible. The improved images are assessed quantitatively using the peak signal-to-noise ratio and the structural similarity index. The suggested technique performs better with an SSIM mean of 0.45 and a mean PSNR of 16.20 dB. For binary classification, AlexNet is employed, and its testing accuracy for improved and unimproved images is 90.37% and 85.90%, respectively. This shows how effective the suggested multi-level GAN is in improving biological pictures while maintaining structural details and significantly reducing artifacts. To get beyond the limitations of training data, future research may construct a semi-supervised augmentation network or an unsupervised one.

A unique method called Synthetic-to-Real Test-Time Training, for improving the functionality of liver cancers models for segmenting images that were trained on fake images, is proposed in [22]. Liver Tumor Segmentation Benchmark and the Medical Segmentation Decathlon Task 08 datasets are used for testing. There are three classes, a task for segmenting tumors, and specific adjustments. The resulting model, which was developed using artificial images, successfully generalizes to actual test photos.

A method of automatically segmenting hepatic lesions on MRI without contrast is proposed in [9]. DUN segment and Radiomics-guided discriminator are both components of Radiomics-guided DUN-GAN. There are 201 abdominal CT scans with contrast in the LiTS dataset. SVM and two classes of pixels are used. Results of 93.470.83% were obtained from segmenting lesions in non-contrast images of 250 clinical cases (Table 1).

3.2 Convolutional neural network

CNN has used DL method architectures. CNNs are employed in the application of computer vision such as video and image segmentation, classification, and detection. The convolution, input, pooling, and activation of Rectilinear Units and layers are fully linked and are all components of the design CNN. The picture problems', breadth, height, and depth make up the three input dimensions architecture of CNN. The image is fed into the convolutional neural network's layers one at a time. Each time a picture cycles through these layers, the mappings feature is learned. These feature maps include the most crucial information about pictures.

An MRI dataset to classify and predict liver failure using an ensemble and DL-based technique (EL-CN) is used in [28]. The risk to human life is decreased by early identification of liver failure. We developed a powerful hybrid technique combination for prediction and classification. The EL-CN is made up of Ensemble Learning, Convolutional Neural Networks, and Short Neural Networks. A range of features are used by Ensemble Learning (EL) approaches to forecast liver failure. The several types of liver problems and Outcomes with metrics rates include cirrhosis is 98.8%hepatiti 98.6%, and fatty liver is 98.4%. Future studies will also consider a range of actual characteristics and the other early signs of liver failure.

In another research, a deep attention-based adaptive multimodal fusion model is proposed in [23]. Discover how to enhance the performance of multimodal fusion-based lesion characterization. For grading hepatocellular carcinoma, a deep supervision net with attention-guided adaptive multimodal fusion is suggested. The attention-based adapted feature synthesis and the attention-guided deep supervision net modules are components of the proposed framework. The outcomes of grading clinical HCC with contrast-enhanced MR demonstrated the potency of the proposed method. To improve the effectiveness of the characterization in the future, the proposed methodology can be combined with the correlated and individual feature analyses that have already been investigated.

The CAD approach is proposed in [23] that merges deep and handmade aspects to differentiate between typical FNH and HCC. The trained truncated 3-D-CNN extracts the deep features. The modern hand-crafted methodology is used to extract the hand-crafted qualities. For diagnosis, they are fed and fused to a classifier. Many classifiers have produced outstanding results, proving the supremacy of the fused features. One dataset was used for model optimization, and the other was used for performance evaluation. The SVM and MLP both have improved and relatively comparable average classification performance. The three classifiers' performances were comparable, demonstrating the robustness and representativeness of the fused features. The experiment's findings showed 94.40% accuracy, 94.76% sensitivity, and 93.62% specificity.

A unique deep classifier composed of deep convolutional neural networks (CNNs) that have undergone pre-training is proposed in [3] to classify the liver status. Deep convolutional neural networks like ResNet18, ResNet50, ResNeXt, ResNet34, and AlexNet can be tweaked to provide efficient classifiers on tiny datasets of medical. Two-class are normal or hepatitis and normal or cirrhosis, and cirrhosis or hepatitis) and three-class is cirrhosis or hepatitis or normal classifiers were trained to identify between these liver pictures. When liver photos were divided into three classes using ResNet50 and a hybrid classifier, the experimental findings showed an accuracy of 86.4%. The findings demonstrate that the first group's sensitivity and specificity for the differentiation between cirrhosis liver and normal, as well as between hepatitis liver and normal are 90.9% and 86.4%, respectively. Future research may yield better results if deep features and texture characteristics are combined with access to a huge dataset.

In another research [24], GoogleLeNet is used to categorize photos of HCC histopathology (Inception-V1). First, the training model containing a 25-image was tested using four fresh pictures. The new photos passed the assessment with accuracy scores of 91.37% (2.49), 92.16% (4.93), and 90.57% (2.54). Although it has been demonstrated that the amount of training data has a favorable correlation with deep learning classification performance. The purpose of the model is to examine brand-new pre-trained models and automatic labeling techniques to enhance labeling and training using substantial HCC histopathology imaging datasets.

A 4D DL model is proposed in [25], that autonomously segments liver tumors better than some other networks. With the use of a module of the C-LSTM network that leverages time domain data and a module of 3D CNN that extracts spatial context of 3D, our method creates 4D data to aid in segmentation. The suggested deep learning, which utilizes 4D data on dynamic contrast-enhanced MRI images, aids in liver tumor segmentation. It has three classifications: hepatic tumor categorization, patient survival prediction, and therapy response classification. The suggested model beat the RA-UNet model, 3D U-net model, and other model studies ablation in both external and internal test sets. It segmented liver tumors with a Dice score of 0.8250.077, a volume similarity of 0.8910.080, and a Hausdorff distance of 12.848.14 mm. The prediction could be substantially sped up in the future by utilizing the input picture patch's center three slices as opposed to the single slice used by the current algorithm.

The setup and Liver Tumor Segmentation Benchmark results are presented in [20]. The picture collection, developed in partnership with research institutions, and seven hospitals is varied and includes secondary and primary tumors of different sizes and shapes, as well as lesion-to-background levels. After being trained volume set of 131 computed tomography, a total of 75 liver tumor segmentation and submitted liver algorithms were put to the test with 70 unidentified test pictures taken from distinct patients. The algorithm segmentation earned a 0.963 Dice score whereas the algorithm of tumor segmentation s received Dice scores of 0.674 and 0.739, 0.702. Important insights gathered from hosting LiTS will help those in charge of planning the next medical segmentation benchmark challenges. Furthermore, future challenges should take this parameter into account because the problem of tumor detection has clinical relevance.

In another research [18], a unique, robust architecture uses thrice input pictures than simply one image of CT is suggested to automatically identify the liver border and tumors in abdominal CT scans. To create a clearer liver boundary, our method first used a normalization technique to the original image. Then, to obtain a more important image, a new approach (LDOG) was utilized to encode images. The original image and the two additional photos were then used to train a fresh two-path CNN architecture. In this study, we created a novel process to categorize every pixel in the image into one of three classes liver border, tumor border, or other tissues using a mix of local and global information. The proposed innovative architecture for tumor and liver segmentation was tested using a dataset of 1000 patient cases with more than scan slices 20,000. The suggested approach demonstrates that providing more representations of the image is crucial before trying to extract significant data from it (using specific encoding methods). Further research on this would require a thorough analysis. According to the facts previously given, the method of DBN-DNN fared the worst out of the eight approaches.

A study in [6] uses the Hybridized fully convolutional neural networks (HFCNN) for liver tumor segmentation to solve the present issue of liver cancer. In terms of semantic segmentation, HFCNN has been employed as a powerful technique for the analysis of liver cancer. The ability to distinguish between benign liver and cyst metastases from colorectal cancer has been explored using CT abdominal scans, a deep end-to-end learning technique of the liver. Three-fold cross-validation tests have been conducted on a small dataset. Measurements of the liver volume produced by the algorithm were 97.22% highly accurate. The study's average Dice coefficient of 0.92 showed how accurate the segmentation approach was. Modern spatial and three-dimensional knowledge will be used in neural network identification in the future.

The parameter settings are used by a CNN built on a 2.5D model to automatically segment the liver and tumors [26]. The application of the 2.5D model produces encouraging outcomes because the network can have a wider and deeper network design while still supporting the 3D information. It makes use of 2.5D neural networks. Networks are tested and trained using tumors and the challenge of the liver segmentation dataset. The findings of the paper demonstrate that, in terms of dice score, networks with several stacked slices can outperform networks with a single slice. However, more research on the method is needed to improve the method's performance. If needed, liver detection can be used to speed up segmentation processing.

The TA-Net framework is proposed in [8] to autonomously segment liver tumors on computed tomography images. For patient monitoring and treatment planning, radiologists can utilize this paradigm to effectively assess the burden of liver tumors from typical varied clinical data. In our study, we segmented liver cancers using a new technique, contrast-enhanced abdominal computed tomography images, and open datasets are available. This collection contains 131 CT pictures from various clinical locations throughout the world. The examination of visualization outcomes demonstrates the efficiency of our attention modules and the comprehension of CNNs segmentation of liver tumors.

The approach for automatically segmenting liver lesions in CT scans is suggested in [16]. The suggested technique, which demonstrates two deep convolutional neural network models, is broken down into five fundamental steps: picture capture, image pre-processing, initial RetinaNet segmentation, lesion segmentation using segmentation refining, and U-Net. The suggested method was tested on a total of 131 CT scans from the LiTS dataset, and the best results had the following metrics: a sensitivity of 83.86%, a

Matthews correlation coefficient of 83.62%, a Dice coefficient of 82.99%, a specificity of 99.96%, a relative volume difference of 1.69 a volumetric overlap error of 27.89%. The parameters of the two CNN models will be automatically optimized in future work (RetinaNet and U-Net). Using active contour techniques is another method for improving the delineation of segmentation borders.

An idea of a metaheuristic algorithm for convolutional neural network optimization using the Shuffled Frog-Leaping Algorithm is discussed in [27]. A CNN training issue for the SFL approach is first created. This approach is then used to calculate the ideal bias and weight values. Theoretically, there are parallels between the SFLA and particle swarm optimization (PSO). In this study, a previously untrained conventional CNN structure is trained using the well-known Shuffled Frog-Leaping Algorithm (SFLA), which was inspired by nature (LeNet-5). The training strategy is examined using four distinct datasets. The outcomes show that the suggested algorithm has outstanding approximation and classification accuracy in its mechanism. Finding the right SFL algorithm parameters has to be researched for future research. However, results can be improved by investigating the ideal parameters for the number of training batches, pooling type, kernels, and neurons in the hidden layer in the convolutional layers. It would be worthwhile to conduct more studies on this method's optimal tuning utilizing various datasets, such as CKP, ORI facial expression dataset, and ImageNet.

A method that will help with the quick identification of patients with liver cancer is discussed in [2]. In this research, a convolutional network is used to categorize several organs in 3D CT scans of people who may have liver cancer. The dataset of the Cancer Imaging Archive (TCIA) of 63503 CT images of patients with liver cancer was used to validate the proposed method. Using convolutional neural networks (CNNs), images of computed tomography (CT) liver cancer are categorized. Softmax classifier is used in the network, and Adam optimizer is used in the training algorithm to train the network in the classifier over three classes of organs: liver, lung, and bone. When training the convolution network using the volume slices of data-augmented, the outcome indicates a highly accurate validation of 99.1%, compared to an accuracy of 98.7% when utilizing the volume slices that were generated from the beginning. The test accuracy for the dataset with data augmentation for the 93.1% volume slice is higher than for other volume slices. However, the proposed work has the limitation of size, which is small, generating poor classification results. Also, it is limited to only CT scan images.

3.3 GoogLeNet

In a research [24], GoogleLeNet was used to categorize photos of HCC histopathology (Inception-V1). First, the training model containing a 25-image was tested using four fresh pictures. The new photos passed the assessment with accuracy scores of 91.37% (2.49), 92.16% (4.93), and 90.57% (2.54). Although it has been demonstrated that the amount of training data has a favorable correlation with deep learning classification performance. We intend to examine brand-new pre-trained models and automatic labeling techniques to enhance labeling and training using substantial HCC histopathology imaging datasets.

A method for categorizing liver carcinoma automatically is introduced in [28]. By learning designs and parameters, the detection system has been built to exhibit satisfactory performance and is computationally efficient. To improve performance, preprocessing improves CT scans with little contrast and filters noise. The algorithm created performs better and has an improved approach suitable for real-time medical applications, according to a study of networks in the 3D-IRCADB database. The discrete classes involved in CT image categorization have employed transfer learning to alter the UNet and Google Net designs. The training result is 0.9511 and the validation set of results is 0.9633. In the future, combining Google Net with U-Net could be considered to increase accuracy while lowering the complexity of results.

3.4 U-Net

U-Net architecture is used for biological image segmentation. The U-Net design utilizes two symmetric paths, one on each side, and is based on a convolutional neural network. On the right, the path that grows is the decoder, and the one that contracts is the encoder (on the left). Contextual information is encoded by the encoder, while local information is encoded by the decoder using transposed convolutions. Convolutional and max-pooling layers are combined with ReLU activation, concatenation, and upsampling in these encoder and decoder paths.

In a paper [29], Modified U-net outperforms other DL models in the segmentation of tumor and liver, achieving strong dice similarity coefficient (DSC) scores of 89.38%, respectively, on the dataset of live liver segmentation benchmarks (LITS) of size 256. Using deep learning methods, the 3Dircadb and LITS datasets were segmented into the liver and tumor regions. Using an improved modified Unet approach, the liver and tumor could be clearly distinguished from one other in LITS 2D CT images. The liver and tumor both had dice similarity coefficients of 96.15% and 89.38%, respectively. Also, a 3DIRCADb dataset was utilized to assess the approach, and the outcome demonstrated that perfection is effective.

In a study [28], a method for categorizing liver carcinoma automatically is described. By learning designs and parameters, the detection system has been built to exhibit satisfactory performance and is computationally efficient. To improve performance, preprocessing improves CT scans with little contrast and filters noise. The created algorithm performs better and has an improved approach suitable for real-time medical applications, according to a study of networks in the 3D-IRCADB database. The discrete classes involved in CT image categorization have employed transfer learning to alter the UNet and Google Net designs. The training result is 0.9511 and the validation sets of results are 0.9633. In the future, combining Google Net with U-Net could be considered to increase accuracy while lowering the complexity of results.

3.5 LSTM

An RNN technique known as Long short-term memory (LSTM) facilitates the usage of feedback links as a general-purpose computer. The processing of sequences, pattern recognition, and images are all applications of this technique. Input, output, and forget gates are the three primary components of an LSTM. The LSTM may retain computations performed in a previous time step and decide when to let input into the neuron. One of the LSTM method's key advantages is that all of these choices are made based solely on the current input.

A 4D DL model that autonomously segments liver tumors better than some other networks is suggested in [25]. With the use of a module of the C-LSTM network that leverages time domain data and a module of 3D CNN that extracts spatial context of 3D, our method creates 4D data to aid in segmentation. The suggested deep learning, which utilizes 4D data on dynamic contrast-enhanced MRI images, aids in liver tumor segmentation. It has three classifications: hepatic tumor categorization, patient survival prediction, and therapy response classification. The suggested model beat the residual attention-aware U-Net (RA-UNet) model, 3D U-net model, and other model studies of the ablation in both external and internal test sets. It segmented liver tumors with a Dice score of 0.8250.077, a volume similarity of 0.8910.080, and a Hausdorff distance of 12.84814 mm. The prediction could be substantially sped up in the future by utilizing the input picture patch's center three slices as opposed to the single slice used by the current algorithm.

3.6 Deep recurrent neural networks (DRNNs)

RNN technology can recognize a variety of sequences and patterns, including speech, handwriting, text, and others. The structure's cyclic connections, which process incoming data sequentially using recurrent computations, benefit from RNN. RNN is simply a Convolutional neural network that has been stretched over time since it has edged that feed into the next time step rather than the next layer in the same time step. The outputs are calculated using the state vectors that are saved for each of the previous inputs in hidden units.

An image enhancement method for CT low-dose scans that is superior to DRNN is presented in [13]. The approach interweaves many back projections and residual network enhancement modules to form a deep network that integrates image-enhancing tasks. For low-dose CT pictures, this research proposed an enhanced deep neural network-based image-enhancing technique. The training dataset offered consists of filtered back-projection full-dose and quarter-dose CT scans from 10 ACR-certified phantoms and 10 patients with liver lesions. The suggested technique outperforms other well-known image enhancement algorithms in terms of performance and preservation of low-dose CT images' detail features, according to evaluation and real-world data.

3.7 Transfer Learning

One key technique in DL networks for models with fewer data is transfer learning. The extensive library of real images serves as the pre-trained algorithms' source of attribute learning. Transfer learning's main goal is to share knowledge between networks that have already received training, cutting down on training time. The two main methods of transfer learning that have so far been established are network tuning and feature extraction utilizing the same pre-trained network. The benefit of fine-tuning is that it eliminates the need to train a deep network from scratch and enables the transfer of existing features to the next model.

A technique for categorizing liver cancer histopathology pictures using MIL and mixed transfer learning with just global labels is proposed in [30]. The experiment's findings demonstrate that the technique is accurate at differentiating between images of aberrant and normal liver histology. Large, properly labeled histology images that have been annotated by skilled pathologists are not necessary with our method. Although the TCGA dataset's liver cancer tissue regions lack precise segmentation annotations, it does provide labels that list the different WSI kinds. From the histopathological photos, three datasets of 0.15, 0.15, and 0.7, which stand for validation, testing, and training datasets, were generated at random. To improve its functionality for medical image segmentation and categorization applications, our method may be used with other instances of learning multi-cluster, EM-based, and K-means, strategies for patch selection. The final F1 score was 0.99, the recall was 1, and the accuracy was 0.98.

3.8 Random survival forest (RSF)

The random forest is an ensemble model that may also be used as a sort of nearest-neighbor predictor. The fundamental idea underlying ensemble approaches is that various models will combine to create a potent model. Together with the random forest, a decision tree using the usual ML technique is supplied. Starting at the top of the tree with an input, this algorithm buckets the data into progressively smaller sets as it descends. The random forest expands on this concept by combining the ensemble concept with trees. A random forest classifier provides the advantages of quick running times, imbalance, and handling of missing data. The testing data or new dataset is dispersed along with the newly created subtrees in the random forest. Any decision subtree within the forest may choose the dataset's class.

The autonomous hepatocellular carcinoma staging model developed in [19], comprises a revolutionary machine-learning technique that is significantly more clinically comprehensive than any other staging system in use today. A new staging hepatocellular carcinoma approach based on patient survival embeddings and RSF generated using B-spline fits of cumulative hazard functions is proposed. The proposed methodology is completely autonomous, comprises a vast array of characteristics that much outnumber those in any existing staging system, and has the potential to be applied to other cancer kinds. The resulting staging method works noticeably better than the Barcelona Clinic Liver Cancer staging system approach at differentiating between patients in various phases. We are confident that more work will result in an even more precise staging mechanism. However, more work will result in an even more precise staging mechanism. Also, it's crucial to be able to combine numerous factors to increase accuracy, even though it's crucial to find more concise and intelligible models that keep high accuracy.

3.9 K-Means Clustering

Data clustering based on the nearest neighbor is typically accomplished using the unsupervised learning algorithm K-Means. Depending on how similar the data are to one another, they can be divided into k clusters. As K is an integer, the algorithm requires knowledge of its value. The K-mean clustering algorithm, which is the most popular, may select the best cluster for fresh data based on most of the distance. All the points are first allocated to the closest centroids, and the centroids are then once more computed for the newly assembled group. The initial selection of the k-cluster centroids is done at random. Given that some of them are influenced by centroids, K-means are more susceptible to noise and outliers. The K-means technique has the benefit of being easy to use, simple to comprehend, and efficient in terms of computation. The difficulty in estimating K values is this method's drawback. The efficiency of globular clusters is compromised.

A cost-effective liver cancer prediction model by analyzing epidemiological data using an algorithm of machine learning has been developed in [19]. The model is employable as a window to raise awareness of cancer prevention and as a doorway into medical checkup facilities to encourage people to lead healthy lifestyles and to pay attention. This could be seen as the beginning of a general campaign to prevent cancer. Hospitalized patients undergo additional testing (such as liquid biopsies and medical imaging), and physicians can employ customized, preventive, and predictive medicines using this knowledge to predict the start of liver cancer. The early Diagnosis and Treatment of Urban Cancer (EDTUC) dataset, which is highly skewed, makes it difficult to generate precise predictions about the likelihood of developing liver cancer. Under-sampling techniques (label-aware LVQ and K-means++ prototypes) are used to rebalance the dataset to overcome the class-imbalance issue. However additional professional skills in data-driven models can be incorporated to address the issue of class inequality and improve interpretability.

Table 1. The Taxonomy table for Liver Cancer

Model	Research Paper	Performance metrics	Value
Generative adversarial networks (GAN)	[7]	Accuracy	Medium
	[9]	Similarity Co-efficient	High
Convolutional neural network (CNN)	[11]	Accuracy	High
		Sensitivity	High
		Specificity	High
	[12]	Accuracy	Medium
		Sensitivity	Medium
		Specificity	Low
	[3]	Accuracy	Medium
		Sensitivity	High
		Specificity	Medium
	[13]	Accuracy	High

		Sensitivity	High
		Specificity	High
	[4]	Accuracy	High
	[16]	Accuracy	High
	[14]	Accuracy	High
	[31]	Accuracy	Medium
		Sensitivity	Medium
		Specificity	High
	[1]	Similarity Co-efficient	Medium
		Volumetric Overlap Error	Low
		Relative Volume Difference	Low
	[2]	Accuracy	High
	[14]	Accuracy	High
		Similarity Co-efficient	Low
		Accuracy	High
		Similarity Co-efficient	
GoogLeNet		Accuracy	High
	[13]	Sensitivity	High
		Specificity	High
	[14]	Accuracy	High
U-Net		Similarity Co-efficient	Low
	[15]	Similarity Co-efficient	High
Deep Recurrent Neural Network (DRNN)	[17]	Accuracy	High
Transfer learning (TL)	[18]	Accuracy	High
Random survival forest (RSF)	[5]	Accuracy	Medium

In Table 1, the range of values used for High is greater than 90, for medium range is between 80 and 90, and for low is smaller than 80.

4. Performance Metrics

By calculating assessment measures based on four significant outcomes, the efficacy of any abdominal image-based segmentation or classification system can be assessed: false positives (fp), true positives (tp), false negatives (fn), and true negatives (tn). The proposed system's performance is assessed using the following metrics:

4.1 Accuracy:

The use of accuracy in the proposed system classes should be properly determined. We determine the proportion of real positive to real negative cases across all cases examined to evaluate the precision of a test set.

$$\text{Accuracy} = \frac{tp+fn}{tp+tn+fp+fn} \tag{1}$$

4.2 Sensitivity:

Sensitivity measures a system's ability to the percentage of true Positives used to accurately classify the classes. It is determined by:

$$\text{Sensitivity} = \frac{tp}{tp+fn} \quad (2)$$

4.3 Specificity:

Specificity, which measures how well a model can categorize the actual class, can be calculated as follows:

$$\text{Specificity} = \frac{tn}{tn+fp} \quad (3)$$

4.4 Precision

The following formula is used to compute the true positive relevant measure for precision:

$$\text{Precision} = \frac{tp}{tp+fp} \quad (4)$$

4.5 F-score:

The F-score is used to check the accuracy of the test set. The harmonic mean of precision and recall is calculated by:

$$F\text{−score} = 2. (\text{Precision. Recall} / \text{Precision} + \text{Recall}) \quad (5)$$

4.6 Dice coefficient:

The Sorensen-Dice coefficient, commonly known as the overlap index, is a statistic for assessing the accuracy of the segmentation of medical images. Using the Dice, whose definition is as follows, it is possible to determine the pair-wise overlap of the repeating segmentation:

$$\text{Dice} = \frac{2tp}{2tp+fp+fn} \quad (6)$$

5. Discussion and Future Work

One type of cancer that begins in the liver cells is known as liver cancer. HCC is a common type of liver cancer, which makes up about 75-85% of all cases. Other types of liver cancer include cholangiocarcinoma and angiosarcoma. Although various risk factors can raise the likelihood of developing liver cancer, the actual etiology of the disease is not always established. Some of the most common risk factors include chronic infection with Non-alcoholic fatty liver disease, hepatitis B or C, Heavy alcohol consumption, exposure to aflatoxins (toxins produced by certain molds), Obesity, and Diabetes. Symptoms of liver cancer may include pain in the abdominal region, weight loss, nausea, loss of appetite, vomiting, fatigue, and jaundice. Treatment of liver cancer depends on several factors, such as the location and size of the tumor, the type of cancer, and the overall health of the patient. Options of Treatment include therapy targeted, surgery, chemotherapy, and radiation therapy. In some cases, a combination of treatments may be used. Prevention of liver cancer includes reducing exposure to risk factors such as hepatitis B and C, limiting alcohol consumption, maintaining a healthy weight, and avoiding exposure to toxins like aflatoxins. Regular screenings and check-ups may also be suggested for individuals with a great risk of developing liver cancer. We have classified this paper into two categories: liver cancer detection using deep learning and machine learning models such as generative adversarial network (GAN), LSTM, Deep residual neural network, transfer learning, Random survival forest (RSF), K-Means Clustering and convolutional neural network (CNN) which include GoogLeNet and U-Net.

In the future work on a model-based automated technique for classifying several organs from 3D CT liver cancer pictures. The technique enables the model to distinguish between valuable slices and those that are not. An oncologist can focus more on a candidate slice by using the limited subset of data provided from the large slice instead of scrolling through hundreds of slices, dataset. A collection of 3D CT liver cancer pictures was used to train the network. These images were obtained using a variety of multi-slice CT scanners with various radiation doses and scanner settings. We plan to make our TA-Net model available on a platform for remote online diagnostics after designing a 3D version of it and further improving and extending it to other diseases and modalities.

6. Conclusion

One of the leading causes of death around the globe is liver cancer. Liver cancer is the fourth most prevalent cause of cancer-related deaths worldwide and the sixth most often diagnosed malignancy, by the WHO (World Health Organization). In this paper, we have discussed machine learning and deep learning-based techniques such as generative adversarial network (GAN), LSTM, Deep residual neural network, transfer learning, Random survival forest (RSF), K-Means Clustering and convolutional neural network (CNN) which include GoogLeNet and U-Net to detect liver cancer.

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