Short Communication

BIOMEDICAL Journal of Scientific & Technical Research

ISSN: 2574 -1241

DOI: 10.26717/BJSTR.2023.51.008073

Liver Cancer Detection & Automatic Liver Segmentation by Power of AI

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ARTICLE INFO

Received: June 16, 2023

Published: June 26, 2023

Citation: S Faiza Nasim, Sana Fatima and Umm E Kulsoom. Liver Cancer Detection & Automatic Liver Segmentation by Power of AI. Biomed J Sci & Tech Res 51(2)-2023. BJSTR. MS.ID.008073.

ABSTRACT

This article has discussed the difficulties in distinguishing liver tumors from computed tomography images. as low As well as the liver tumor image being complex and variable in terms of size, shape, and location, there is little contrast and blurring of the boundary between liver tumors and healthy tissues in Cs. We have covered the process of diagnosing lung cancer in this paper because the condition can produce a wide range of symptoms. However, these symptoms are typically brought on by benign tumors or other issues rather than cancer. In the absence of earlier detection of malignant nodules, survival rates significantly rise. Artificial intelligence has enabled radiology specialists to offer much more value to their patients. Our reporting and workflow can be greatly enhanced by incorporating data from artificial intelligence algorithms. Incorporating data from artificial intelligence algorithms can significantly improve our reporting and workflow. Although AI for imaging will not be available all at once, practices that use it now will be well-positioned to lead the way in healthcare in the future. This paper highlights the list of radiologist sensors that are used with radiologist systems. We discussed the methods Deep Learning Neural Networks (CNN) [1] use to diagnose and treat liver disease in Section 2.0. In Section 4.0, we have concluded results by applying quantitative evaluation, mean surface distance (MSD), and Hausdorff distance (HD).

Keywords: Artificial Intelligence (AI); Deep Learning Neural Network (CNN) For Liver; Mask R-CNN; Data Processing and Feature Technique; Activation Function; Computed Tomography (CT)

Abbreviations: MSD: Mean Surface Distance; HD: Hausdorff Distance; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; MRA: Magnetic Resonance Angiography; SVM: Support Vector Machines; RF: Random Forest

Introduction

Liver diseases can be diagnosed through various medical imaging schemes such as CT scans, ultrasounds, and MRIs [2]. Dynamic contrast-enhanced MRI provides the most comprehensive information for the differential diagnosis of liver tumors [3]. However, personal opinion can influence an MRI diagnosis. Lung cancer can cause many different symptoms. Most frequently, these symptoms are not caused by cancer but by harmless tumors or other problems. If early detection of malignant nodules can't be achieved, then survival rates will steadily increase. Radiologist sensors used for radiologist systems are computed tomography (CT) scans, ultrasound, magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), and nuclear medicine scans (bone scans and thyroid scans).

Methodology

Our objective is to diagnose liver cancer in its early stages, and treatment can improve the survival rates of liver cancer patients. Accurate diagnosis of liver diseases and treatment of liver cancers to assess the use of artificial intelligence systems in examining HCC (hepatitis C) liver mass images in the diagnosis of cancer and evaluating the accuracy level of AI systems and their performance. Transforming cancer diagnostics and treatment through the power of deep learning with reinforcement learning [4].

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Proposed Solution Use Case

In Figure 1 it's clearly visible how liver damage occurs in every stage, converting it from normal to cirrhosis. Most authors have used a single model approach and use deep learning neural networks (CNN) [1] for liver disease diagnosis and treatment. Here in Figure 2, both anterior and posterior views are highlighted, which will be used in automatic liver segmentation treatment [5]. Some authors have used K-Mean Clustering, Support Vector Machines (SVM), and Random Forest (RF) modules for finding liver diseases (classify fatty liver disease, jaundice, and hepatitis), but it's considered the traditional method [5]. A deep-learning neural network [6] (CCN) can be used for finding and analyzing the hepatitis C stages. Reinforcement learning can be efficiently used for automatic liver segmentation. Deploy deep reinforcement learning into two challenging and representative medical object detection and segmentation tasks [1].

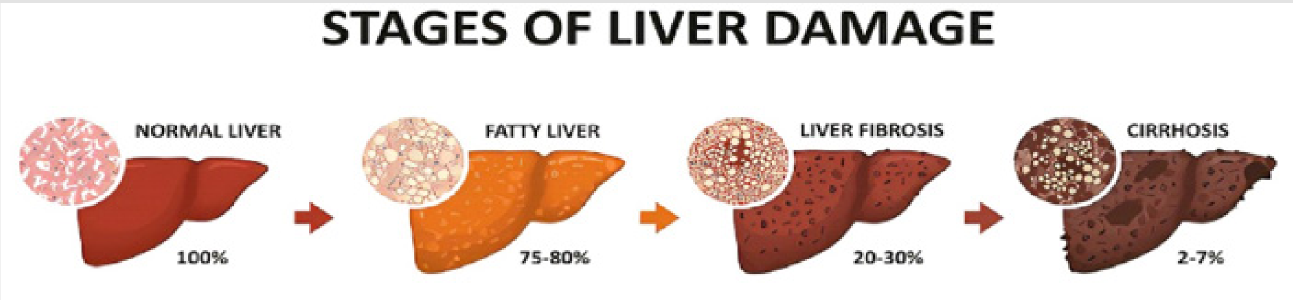

Figure 1: Diagnostics Classification (Liver Disease Diagnostics Classification).

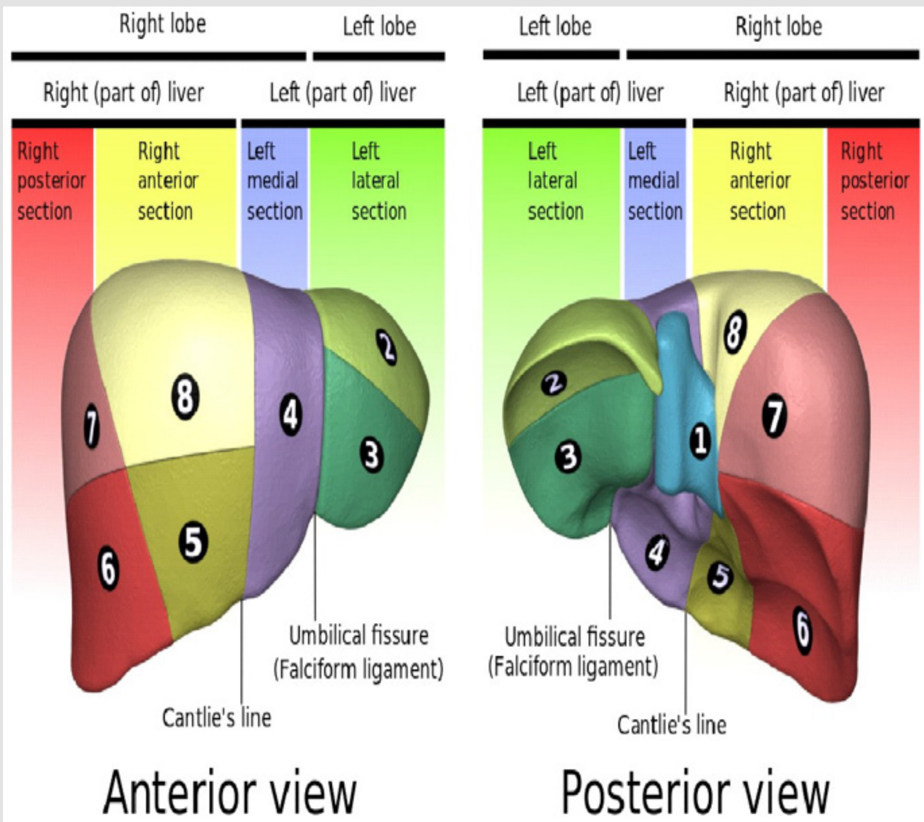

Figure 2: Liver Segmentation.

Deep Learning Methods for Medical Object Detection & Segmentation

- Fully Convolutional Network methods are the pixel-to-pixel network in which every layer is a convolutional layer [4], they input the medical image and output the same size segmentation directly. The most famous FCN method in medical image segmentation [3] is U-Net & others is Dense U-Net, MultiResUNet & Attention UNet . Note that, in such methods, the detection result usually is determined by the surrounding-box of the segmentation.
- Proposal-based methods generate one or several regions of interest (RoIs) as proposals where the desirable object may exist first and then segment the RoIs to obtain segmentation. A typical proposal-based method is Mask R-CNN, which proposes RoIs on the image, segments each RoI, and predicts the bounding box of desirable objects. Based on the mask R-CNN, there are lots of proposal-based methods being proposed, such as HMR-Net scoring R-CNN [1].

Deep Reinforcement Learning for Medical Object Detection

Deep reinforcement learning, as the newest AI technology, has great potential to address the limitations of traditional DL methods. DRL has a sequential process to interact with the task, which allows DRL to gradually understand the intrinsic knowledge about the task and then complete the task effectively. Therefore, in medical object detection and segmentation, compared with traditional DL methods, DRL can gradually approach the desirable object to locate its location by sequentially interacting with the image. This object location facilitates subsequent object detection and segmentation much easier and more accurately. DRL integrates the advantages of reinforcement learning and deep learning to achieve the above sequential process [4].

- Q-learning Network (DQN) which is a value-based algorithm and has been employed in anatomical tumor detection [3].
- Soft Actor-Critic (SAC), which is an AC method. SAC is attracting more and more researchers because it is robust to the hyper parameters and performs stably.
- The 3D-IRCADb-01 database is composed of three-dimensional (3D) CT-scans of 20 different patients (10 females and 10 males) for testing and training the model.
- Use Pre-trained model for feature extraction & feature selection and also used for data pre processing as well as features restoration technique can be used.
- CT value normalization, Gray value interval mapping, image preprocessing & Feature Extracting be used.
- History of patients can be used in Deep Learning Neural Network (CNN)at input layer along with liver disease symptoms and then try to use "Dropout" layer function for reanalysis [5].
- One of the major deep learning techniques named tensor flow technique to investigate images in scan for the task of visualization of abnormal conditions of liver tumor in the context of shape and color towards disease diagnosis as tensor flow for classifying images, detection of objects, and detection.
- SegNet is a semantic segmentation model. This core trainable segmentation architecture consists of an encoder network, a corresponding decoder network followed by a pixel-wise classification layer. The architecture of the encoder network is topologically identical to the 13 convolutional layers in the VGG16 network.

Various data processing and feature extraction techniques of AI are using in liver cancer detection, which include converting images into normalized 3D numpy arrays, resizing, resizing the same resolution in order to apply the same model to scans of different thick thicknesses [6vert all data to Hounsfield units imaginations (pixel brightness transformations/brightness corrections) for brightness corrections (brightness corrections) and gray scale transformation, image filtering, and segmentation [3] (high pass filters (edge detection)) Further, using AI and OpenCV for all general image preprocessing, we can calculate the MD5 hash for each image when there are duplicate images.

Model Architecture

- Network architecture for liver segmentation. In convolutional layers, batch normalization (BN), and ReLU or softmax activation can be used.
- Pooling Layer: The pooling layers aim at reducing the parameter number of big image data. To this end, each feature map generated through feeding the data to single or multiple convolutional layers is then pooled within a pooling layer. The pooling operations obtain small grid segments as input and generate singular numbers for every segment. This is known as subsampling or downsampling, in which dimensionality of every map is minimized while retaining important information. There are different types of spatial pooling, comprising

(1) Max-pooling;

(2) Average-pooling; and

(3) Sum pooling.

Max-pooling obtains the largest value of the considered rectified feature.

- Sequential-Conditional Reinforcement Learning (SCRL) for vertebral body detection and segmentation by modeling the spine anatomy with deep reinforcement learning [4] 2)

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Weakly Supervised Teacher-Student network (WSTS) for liver tumor segmentation [7] from the non-enhanced image by transferring tumor knowledge from the enhanced image with deep reinforcement learning.

- Three-dimensional dual path multistate convolutional neural network (TDP-CNN) [1]. To balance the performance of segmentation and requirement of computational resources, the dual path was used in the network, then the feature maps from both paths were fused at the end of the paths. To refine the segmentation results, we used conditional random fields (CRF) to eliminate the false segmentation [7] points in the segmentation results to improve the accuracy. In this case, We did not use pooling layers, because the pooling operation will result in the loss of the exact location of the voxels, which may harm the accuracy of the segmentation results.

Results & Discussion

In our paper, we have used quantitative methods to quantify the quality of segmentation. Three metrics were retained to quantify the quality of segmentation: the sensitivity, the specificity, and the Simtheitdiceent (DS) as the Jaccard index in some rare cases. Mean surface distance (MSD) and Hausdorff distance (HD) were also implemented for liver cancer detection using artificial intelligence. Similarly, in statistical analysis, detection performance, segmentation accuracy, and dice coefficient evaluate the overlap between the tumor prediction [3] and the ground truth, showing that the value is closer to 1, indicating more tumor pixels in the prediction are correct and fewer tumor pixels in the ground truth are missed. Performance Metric precision, recall, and F1 score give a better intuition of the prediction results compared to the accuracy of AI.

$$Recall\ sensitivity\ = TP/TP + FN$$

$$Precision\ specificity\ = TN/TN + FP$$

$$DSC = TP/TP + FP + FN$$

- Recall measures the rate at which the prediction is corroborated. The value closer to 1 means more tumor pixels are classified correctly.
- Hausdorff distance (95HD) evaluates the respective distance between the tumor boundary in the tumor prediction and the tumor boundary in the ground-truth.

Conclusion

In our paper, we have discussed various image classification algorithms for disease detection and predicted results by applying evaluation metrics to artificial intelligence. Algorithms highlighted in this paper are:

- K Mean Clustering Unsupervised Learning & Support Vector Machine (SVM) & Random Forest (RF).
- Deep Learning Convolutional Neural Network (CNN).
- LSTM (Long Short Term Memory).
- Deep Reinforcement Learning (D-RL).

Acknowledgment

Finally, it is a real pleasure for me to acknowledge the contributions of my amazing partner Umme kulsoom who's working with PAF Kiet. This paper and the research behind it would not have been possible without their extraordinary support. We worked to provide valuable insight into cancer detection using AI techniques.

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ISSN: 2574-1241

DOI: 10.26717/BJSTR.2023.51.008073

S Faiza Nasim. Biomed J Sci & Tech Res