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Liver Tumor Segmentation using Deep Learning Techniques

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Abstract

Liver tumor segmentation plays a critical role in medical imaging analysis, especially in cancer diagnosis and treatment planning. Accurate segmentation of liver tumors is essential. There has been growing interest in developing automated methods for liver tumor segmentation, practically using deep learning algorithms. In this paper, we use the convolutional neural networks (CNNs), on large datasets of liver images, labelled with the tumor regions. A U-net architecture is builtwith cross connections. The encoder and decoder portion of the Unet is built using a 34 layerResNet. The model was trained on Liver Tumor Segmentation challenge (LITS) dataset of liver CT scans and evaluated on a separate test dataset. The results demonstrated that the proposed method produced great segmentation accuracy and an average dice score of 0.95

Keywords: Liver tumor, Image processing, Segmentation, Convolutional neural networks, U-net

Introduction

With an estimated 830,000 new cases and 780,000 deaths each year, liver cancer is the sixth most frequent malignancy and the fourth largest cause of cancer-related death worldwide. Early detection and treatment are crucial in improving outcomes and increasing the chances of survival for individuals with liver cancer. Liver tumors can be beningn (non-cancerous) or malignant (cancerous). The most common type of liver tumor is hepatocellular carcinoma (HCC), which isa malignant tumor that arises from liver cells. The manual segmentation of computed tomography (CT) scans used in current medical practise for identifying the liver is subjective, boring, unreliable, and time-consuming—it can take up to an hour each patient. For the interpretation of CT and magnetic resonance (MR) images, methods including manual or semi-manual segmentation are used. These methods are essentially subjective, operator-dependent, and time-consuming. Computer assisted procedures have been used to improve the radiologist's effectiveness.

In recent years, Convolutional Neural Networks (CNNs) have completely changed the way that medical image processing is done.CNNs are a type of deep learning algorithm that can automatically learn features from images without the need for manual feature extraction. In medical image processing, CNNs can be utilised for a number of tasks, such as image classification, face recognition, neurology, object identification, segmentation, and detection.They can be trained to detect tumors in medical images with high accuracy which can help improve early diagnosis and treatment of various types of cancer.

Here we are using U-Net convolutional neural network architecture which has become popular for its ability to segment images accurately, even with limited training data. It has been used for many different image segmentation tasks, such as satellite image segmentation and medical picture segmentation.Image segmentation is the process of breaking an image up into different sections or segments depending on specific traits like colour, texture, or shape.The goal of segmentation is to extract useful information from an image and make it easier to analyse or understand. U-Net is well-suited for image segmentation tasks because of its ability to attain both global and local information in an image. The network can be trained end-to-end using a loss function that compares the predicted segmentation to the ground truth.

Literature Survey

The CNNs have garnered a lot of attention over the years which led to their consideration for medical segmentation applications. Many researchers used these CNNs in liver tumor segmentation. Here is a literature survey of some of the recent advances in liver tumor segmentation.

[1] This paper considered different models in U-net architecture which are 2D unet, 3D unet and hybrid unet. These models together with ensemble learning models are compared. They achieved highest dice score of 0.6 for the 3D unet model among the others.

[2] In this paper, the authors applied normalization to the CT images. These images are provided for the segmentation algorithms which are spatial FCM algorithm and OTSU threshold. The average dice score is 0.60

[3] This paper proposed a multi-stage deep convolutional neural network(DCNN) model which can be used for segmentation of tumors in the livers. They adapted Unet for segmentation phase and YOLO algorithm for tumor localization. The average dice score per tumor is 0.72

[4] In this paper, the authors took IRCAD Research Institute against digestive cancer dataset. The two models used here are ResUnet and 2D Unet. These two models attained a dice score of 0.95 and 0.92 respectively.

[5] In this paper, the Hybridized Fully Convolutional Neural Network (HFCNN) has been proposed for liver tumor segmentation. a texture 2D CNN based classifier has been

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established to distinguish ROIs into normal and abnormal hepatic lesions. The average dice score is 0.92

Problem Identification

Segmenting liver tumours is a critical step in making an early diagnosis and making a therapy recommendation. The conventional method for getting the desired results is manual segmentation, although it is a labor-intensive operation.Based on the observations from these reference papers, we concluded that the CNNs are showing best results in image processing and segmentation. The different U-net architectures have shown great difference than other models. We use these deep learning techniques on the Liver Tumor Segmentation challenge(LITS) dataset and detect the tumors. The Computed Tomography(CT) scan images from the abdomen are used for the research. We use the convolution neural network models U-net and ResNet combinedly and try to get more accuracy than the other models. [6-14]

Proposed Methodology

In Fig. 1, the proposed methodology's block diagram is displayed. The CT images are provided as the input to the model. In order to achieve better outcomes, normalisation is used during the pre-processing phaseand masks are created for the images. We extract the region of interest (ROI) i.e., liver and apply a u net model to get the segmented tumors.

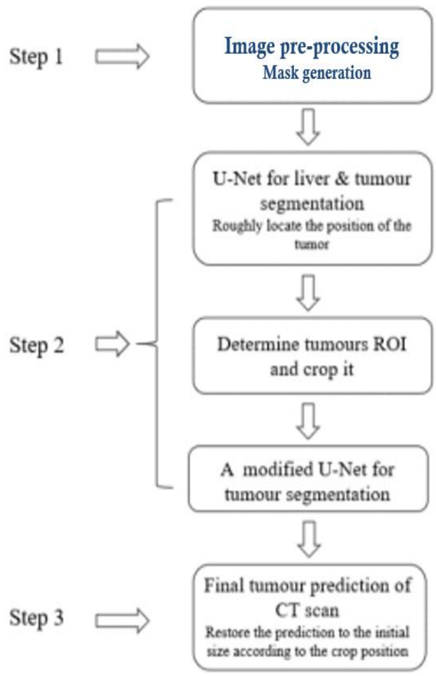

Fig.1. Proposed methodology for liver tumor segmentation

Implementation

A. Dataset

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The dataset used is the Liver Tumor Segmentation Challenge (LITS) dataset. It consists of 201 CT scan images of liver in which 131 are used for training and 70 are used for testing. The scans are acquired from multiple medical centers. Radiologists with the appropriate training identified and confirmed liver and liver tumous in these CT images.Thelocation, size and shape of the tumors can vary widely, making the task of segmentation challenging.

B. Pre-processing

We take the 131 CT scan images and pre-process them before applying the model. These are 3d images with dimensions 512 × 512× 75 voxels. We slice them into 2d images and take every second slice into consideration so that we can reduce the size of data. The masked images have the same size as input images

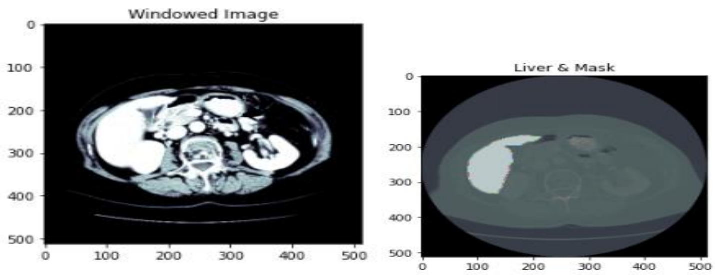

Fig.2. Pre-processed images

C. U-Net

A convolutional neural network architecture called a U-Net was created for the segmentation of biological images. For applications where the output must have that much spatial precision and be the same size as the input, U-Nets have been found to be particularly effective. They are therefore excellent for producing segmentation masks and for producing images with high resolution or colour.Using a sequence of stride two convolutions, the image is captured and downscaled into one or more classes, shrinking the grid size each time.

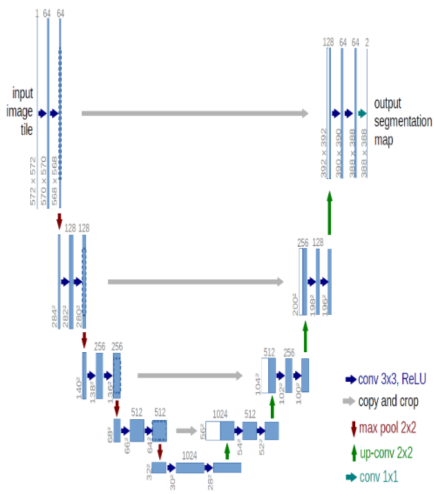

Fig.3. Unet architecture

The U-net consists of a downsampling/encoder part on it's left side and an upsampling/decoder path on the right side which combinedly makes the U shape for the

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architecture .Two 3 x 3 convolutions are applied twice to create the encoder. A ReLU and batch normalisation come after each convolution. After that, the spatial dimensions are condensed using a 2x2 max pooling procedure. Again, we quadruple the number of feature channels while halving the spatial dimensions at each downsampling step.The number of feature channels is cut in half at each stage of the expanding path by a 2 x 2 transpose convolution after an upsampling of the feature map. Moreover, we typically have a 3x3 convolutional layer and a concatenation with the matching feature map from the contracting path (each followed by a ReLU).A 1x1 convolution is employed at the final layer to map the channels to the required number of classes.

ResUNet

ResNet is an architecture for a convolutional neural network made out of a number of residual blocks (ResBlocks).ResUNet is a fully convolutional neural network that is designed to take advantage of both UNet architecture and the Deep residual learning.

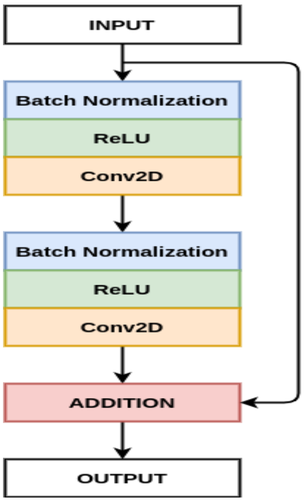

Fig.4. ResNet architecture

Each ResBlock contains two connections from its input, one skipping over the convolutions and functions and the other passing through a succession of batch normalisation, linear functions, and convolutions. An identity, cross, or skip connection is what these are referred to as. Both connections' tensor outputs are combined. A ResNet can be used for the encoder and decoder section of the U-Net to get high performance with fewer parameters. The rich skip connections in ResUNet facilitate greater information flow between layers, which helps in better flow of gradients while training.

D. Training model

The model is trained to segment the images into multi-class labels which are background, liver and tumor. We fed the pre-processed images to the ResUNet model and adjusted the model weights to predict the training images labels correctly. The input feature maps with the channel numbers doubling at each step are applied two convolutional operations and a

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ReLU activation function. The output of each layer is added with it's corresponding input layer in the upsampling process.

E. Evaluation metrics

Dice co-efficient is a spatial overlap index and a reproducibility validation metric which is used as a metric for image segmentation. It ranges from 0, indicating no spatial overlap to 1, indicating complete overlap. The formula for calculating dice score is given by

Dice score = 2*(area of overlap)/(total number of pixels in both images)

Results

In this paper, the proposed system segments the image into liver and tumor with a higher performance using the ResUnet model. This segments the given input into multiple classes i.e, background, liver and tumor.

The model achieved an accuracy of 99% with a valid loss of 0.0029. The dice score is calculated for the multi-class labels and achieved very high value which is 0.95.

epoch	train_loss	valid_loss	foreground_acc	cust_foreground_acc	dice_multi	time
0	0.008922	0.008617	0.916256	0.996919	0.837033	02:52
1	0.005728	0.005427	0.959200	0.997983	0.924770	02:53
2	0.004221	0.004276	0.948672	0.998363	0.945955	02:55
3	0.003554	0.003694	0.954642	0.998562	0.953412	02:55
4	0.003066	0.003439	0.964367	0.998655	0.955975	02:58

Table.1. Results

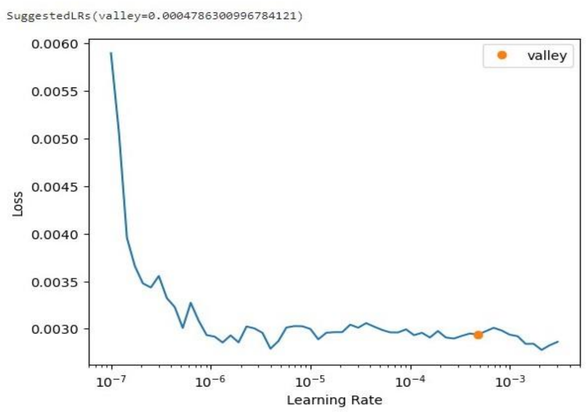

Figure.5. Loss curve

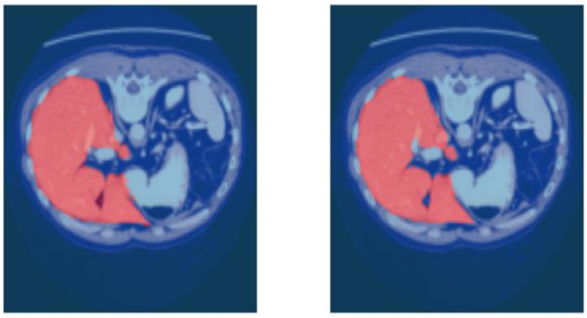

Figure.6. Target and predicted image

Conclusion

The liver is a significant tissue in the human body.It is crucial to find and recognise a liver tumour as soon as possible because liver cancer is lethal.We were successful in achieving our objectives, and CNNs are among the best methods for segmenting liver tumours.In this article, we have developed a ResUnet model to segment the liver and tumors from the CT scan images. It detects the liver and a number of tumors inside it with minimal loss value. The model is trained to achieve more accurate results when compared to the models that came came before. It produced promising results with 99% accuracy. The performance is evaluated using dice score and an average dice score of 0.93 is achieved.

Future scope

In the future, this model can be extended for other medical segmentation challenges for the segmentation tasks. Instead of the CT scans the integration of multiple imaging modalities such as PET-CT or PET-MRI could potentially improve the accuracy of liver tumor segmentation by providing complementary information. Developing more advanced deep learning -based method, such as attention mechanisms or generative adversarial networks (GANs), can potentially enhance the accuracy and robustness of liver tumor segmentation.

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