

Liver Tumor Segmentation using Deep Learning Approach

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Abstract - Segmentation of liver and liver tumors is considered one of the major steps in radiation therapy of hepatocellular carcinoma. The segmentation process is often thought as a monotonous and time-consuming job when done in traditional way. Liver cancer has been as the second most fatal cancer to cause death among the population and also causing more havoc due to the current covid situation. Detection of liver cancer early is usually done using computed tomography (CT). Therefore, there is an urgent need to read, detect, and evaluate CT scans automatically, efficiently, and accurately. However, segmentation of liver and removal from the CT scans is an intricate process, and is still complex. In this work, a deep learning-based approach was proposed to fit liver CT segmentation and classification. The architecture of the deep convolutional encoder-decoder is named ResUNet and 2d-unet, and consists of a hierarchical correspondence of encode-decoder layers. The following architecture was tested on a standard dataset for liver CT scans and achieved tumor True Value Accuracy of up to 99% in the training phase for ResUNet and 92% for 2d-unet.

Key Words: Deep learning, CT images, convolutional neural networks, Liver cancer.

1. INTRODUCTION

As claimed by the World Health Organization (WHO), liver cancer is one of the five mostly viewed common causes of cancer induced deaths in 2018 [1]. Liver and tumor target segmentation represents an important step in successful liver radiation therapy and other interventional procedures. Liver tumors have a deformable shape and high variability of location, as well as poor variation with respect to the surrounding tissues in CT images. Thus, in current scenario, segmentation is mainly done manually, which is time-consuming and expensive [2]. Many papers regarding algorithms for automatic segmentation of livers and liver tumors have been studied to get better idea about the procedure. These model-based methods can often provide good quality of segmentation results, but it involves the use of some parametric steps, which are specific according to the patient and limit the models from being more commonly used.

A CT scan gives comprehensive cross-sectional images of the abdominal region. And this abdominal CT image is further preprocessed in order to remove the extra noise and also to segment the liver tumor from the image. But still, the similarity between tumor and other nearby tissue

in the CT images makes the detection of tumor extremely complex [5]. Therefore, these images need to be preprocessed, augmented and enhanced in order to detect and differentiate cancerous tissue early. Liver tumors show a high variability in their detection and localization. They can be either appear darker than the surrounding healthy liver, in technical terms hypodense or appearing bright i.e., hyperdense. The individual appearance depends on lesion type, state, imaging, threshold method, regional growth, clustering method, etc which can vary immensely from different patients. On top of this, fully-automated system for medical diagnoses and image processing are getting huge demand among medical experts. This research engages to overcome the existing problem and propose a fully automated system for liver segmentation and tumor detection from an abdominal CT image.

2. RELATED WORK

The process of segmentation in medical field has occupied the researchers to extract detailed information about any new findings for many years now. The use of Segmentation has no bounds starting from applications such as identifying objects from videos, face detection, disease detection and fingerprint detection. For example, Jegou et al In their paper have used FCN DenseNet architecture for semantic segmentation of images because of which use of parameters has become more efficient, features are being reused and giving a deep supervised network. The idea of making use of upsampling followed by skip layer and downsampling is giving good classification results [13]. Currently, Machine learning is finding its wide usage in the field of biomedical imaging. Apart from tumor detection it is currently being used in variety of fields. Similarly, Chen et al have also used the same process for femur segmentation scoring a dice index of 0.96 and giving results in a short time of 0.93 s. They have made use of FCN like U-Net embedded with edge detector for feature extraction. These two components are then enhanced together to reduce volume quality loss of femur segmentation which is considered a good case for segmentation [8]. CNN has also been utilized by Liu et al for H3-K27M genotype prediction and also automated segmentation of brainstem gliomas in the paper. The author has used modified U-Net with multiscale feature fusion and local brainstem information addition. The following discussed method was able to achieve a high dice similarity coefficient of 77.03% [10].

The problem of liver tumor segmentation has been around for a long time with great interest received in the medical image computing community. In 2008, the MICCAI 3D Liver Tumor Segmentation Challenge [4] was conducted where both manual and automatic methods were accepted. Among the automatic ones, the ensemble segmentation algorithm using AdaBoost [5] was the best. Other submitted methods focused on adaptive thresholding, region growing, fuzzy or level set methods [6–8].

Given the lack of consistency or fixed pattern of liver lesions, a manual design of powerful features is not trivial. The growth of Deep neural networks (DNNs) is increasing rapidly in the computer vision field because of its ability to gain insight from data. Christ et al. [4] in his research applied two cascaded U-net models to the problem of liver and liver lesion segmentation. The idea employed one model solely for the liver segmentation and a distinct one for the tumor segmentation within a liver bounding box. The final result was cultivated using a 3D conditional random field.

More recently, the Liver Tumor Segmentation (LiTS) challenge in 2017 was conducted with a wide amount of participation. The methods used in both the top scoring researches was DNN. Han, the winner of the first round, made use of two U-Net like models with long and short skip connections, where the first model was used only for coarse liver segmentation allowing the second network to focus more on the liver region. The second model was related to train the model to segment both liver and tumors simultaneously. The two trained models worked in 2.5D. The best among the rest of the participants in the second LiTS round was done by a group from Lenovo Research, China. Their idea basically displayed two neural network models for the segmentation of liver and tumor, respectively. The research consisted of U-Net models working in 2D and 2.5D trained with distinct hyper parameter settings.

3. METHODOLOGY

The structure developed for liver cancer detection to differentiate between malignant and benign tumors is convolutional neural networks. Convolutional neural networks have similarities with traditional neural networks. The general idea of convolutional neural network (CNN) includes multiple layers of convolutional, fully connected, pooling, or fully connected and rectified linear unit (ReLU) layers. Generally, as the network becomes intricate with more parameters, the accuracy of the results increases, along with that it also becomes more computationally complex.

In the first step: 3d volumetric images from the dataset are preprocessed and the steps performed in this were Hounsfield windowing, image and mask normalization, renaming files, merging masks and augmenting the dataset

and then 2d image slices were extracted. This is done to extract the liver pixels from the CT abdominal image which usually includes other organs including stomach, kidney, spleen, pancreas, etc.

In the second step: The sliced images extracted are then trained using 2 cascaded CNNs. The two architectures that were applied on the dataset were 2d-unet and ResUnet, because of which we are able to recognize which model provides more accuracy to segment the liver and extract the region of interest.

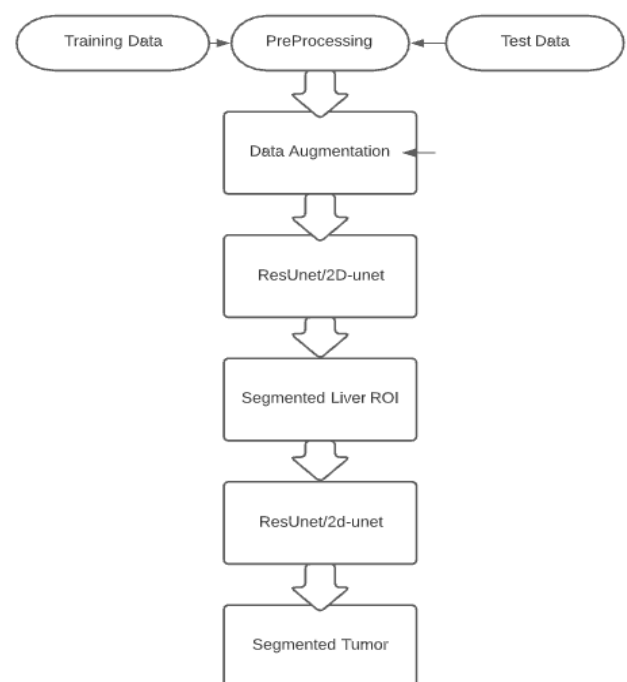


Fig 1: Methodology Diagram

4. LIVER CLASSIFICATION MODEL

4.1 Dataset Description

We used the 3D Image Reconstruction for Comparison of Algorithm and Database 3D-IRCADb01 dataset offered open-source by the IRCAD Research Institute against digestive cancer, which is composed of 3D CT-scans of 10 women and 10 men with Liver tumors in 75% of the cases. The 3D CT-scans are in the DICOM format and are split into 2D-slices with a total of around 2,800 slices each slice has a mask for the Liver, Tumors, Bones, Arteries, Kidneys and Lungs. Here, input size is 512×512, and in-plane resolution has a range from 0.86×0.86 mm² to 0.56×0.56 mm². The count of slices ranges from 74 to 260 with thickness from 4 mm to 1 mm. In this case, data from fifteen patients were used for training (total 2,295 images), and the other five patients' data (total 525 images) were used for testing. There are labeled images and mask images also given that could be utilized as ground truth for the segmentation process.

This study also used the public dataset for the liver and liver tumor segmentation that was obtained from Liver Tumor Segmentation Challenge (LiTS-ISBI2017). The dataset was obtained from 130 abdomen contrast CT scans. The Input size of the images is 512x512, and in-plane resolution has a range from 0.98x0.98 mm² to 0.45x0.45 mm². The count of slices has a range from 75 to 987 with thickness from 5 mm to 0.45 mm. Data from Forty patients were used for training (total 22,500 images) and five patient data (total 2,550 images) were used for validation. The other thirty-five patient data (total 16,125 images) were used for test. More details of the dataset can be found online.

4.2 Data Preprocessing

Images acquired from the two datasets should be processed in order to use them for training and testing the developed algorithm as there is noise present in the image. The 3D-ircadb01 dataset includes up to seven different folders under each patient's data for the tumor masks to identify the anatomical position of the tumor on the liver. Therefore, these tumor masks from those folders should be combined and put into one folder since the main goal is on the segmentation result not on the tumor's anatomical position. The LITS dataset is 3d, so there is no separate mask for the liver as well as its tumor. Instead, they are found under the segmentation folder in the dataset. Since the developed algorithm 2D, so it is essential to convert the data into 2d. Separate mask for the liver and tumor should be prepared. This data preparation was done using Hounsfield windowing, image and mask normalization, augmentation to enlarge the training dataset in order to avoid overfitting, fix class unbalancing and improve training accuracy.

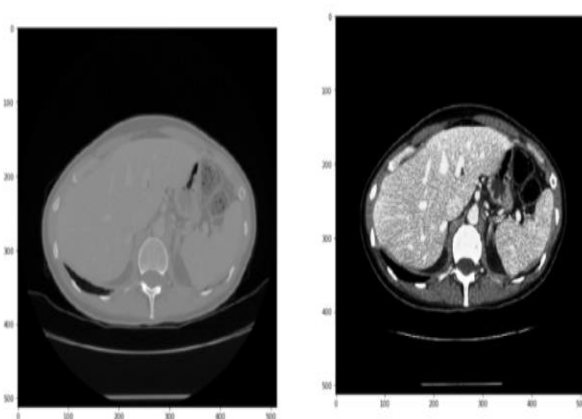


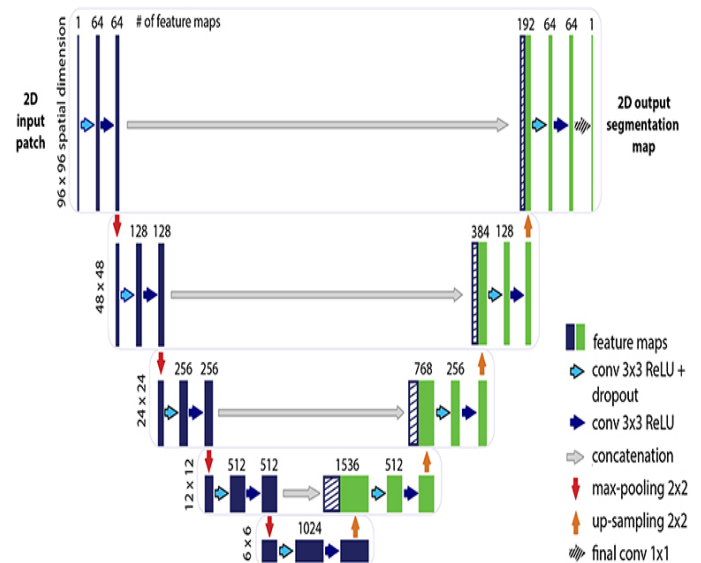
Fig 2: CT slice before and after HU windowing & Histogram Equalization.

4.3 U-Net

The algorithm is based on the UNet architecture which was developed by Ronneberger et al. in 2015. This algorithm comprises of two 2D UNet architectures, for the liver and its tumor respectively. These architectures were

similar to ResUnet designed to segment liver and tumors from the abdominal CT scan images.

For both the segmentation of liver and tumor, U-shaped network architecture is used which is prominently being utilized in medical imaging. U-Net architecture has performed well on various biomedical image datasets. The architecture is displayed in following Figure



.Fig 3: Unet Architecture

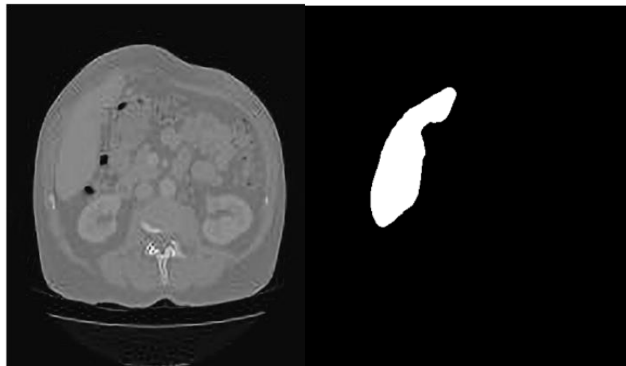
It consists of a contracting path and an expansive path and a bottleneck part also it consists of a total of 23 convolution layers [16]. Every step in the Contracting Path shares a typical architecture of CNNs which consists of bottleneck part also it consists of a total of 23 convolution layers [11]. Every stride in the Contracting Path shares a classic architecture of CNNs which consists of

- Repeated two 3x3 convolutions
- A Rectified Linear Unit (ReLU) refer to following every convolution.
- 2x2 max pooling operation with a stride of 2. 2x2 max pooling operation with a stride of 2.
- Down sampling where the number of feature channels is doubled Down sampling where the number of feature channels is doubled

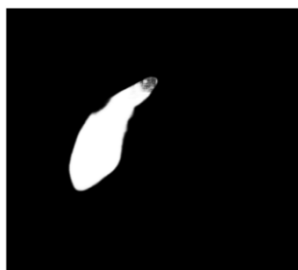
Every Step in the Expansive Path consists of

- Upsampling of the feature map
- 2x2 convolution which decrease the size of feature maps by half
- Concatenation with the cropped feature map

- Two 3x3 convolutions.
- ReLU activation function.



a) Original Image b) Ground Truth



c)Unet

Fig 4: Unet Prediction

4.4 ResUnet Architecture

The second model ResUnet represents a hybrid between the traditional U-Net and the ResNet models, where it replaces convolution blocks with residual blocks giving us the advantages of both models. The residual unit will ease the training of the CNN and the skip connections between low and high levels of the network and inside the residual unit eliminates degradation during information propagation which leads to fewer training parameters.

The ResUnet is constructed from three paths Encoding which encodes the input to a compact representation, decoding which is the opposite of Encoding and categorizes the representation in a pixel-wise fashion and the Bridge which connects the two paths together. compact representation, decoding which is the opposite of Encoding and categorizes the representation in a pixel-wise fashion and the Bridge which connects the two paths together.

Every Residual Block consists of

- Two 3x3 convolution blocks which consists of
 - Batch Normalization Layer. – ReLU activation
 - Convolutional Layer

- Identity mapping

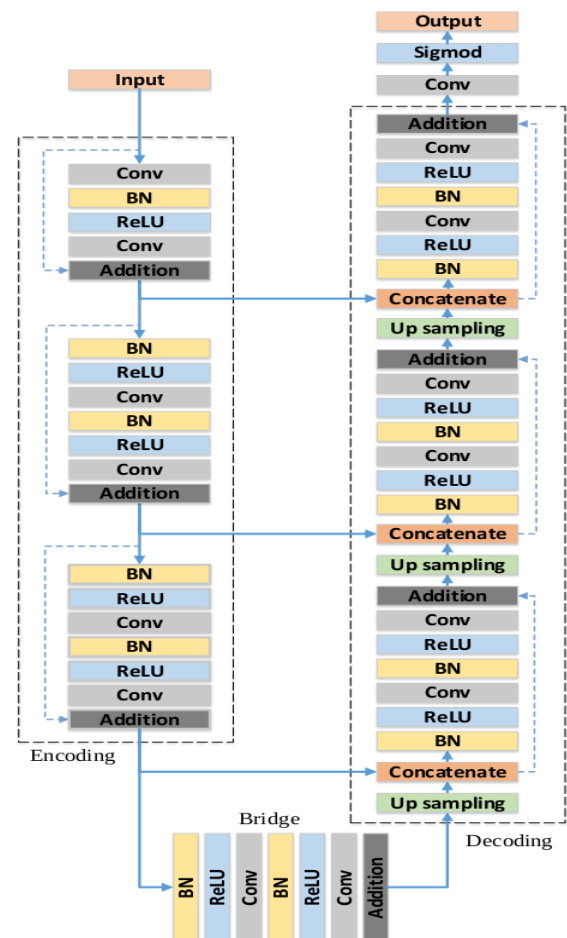
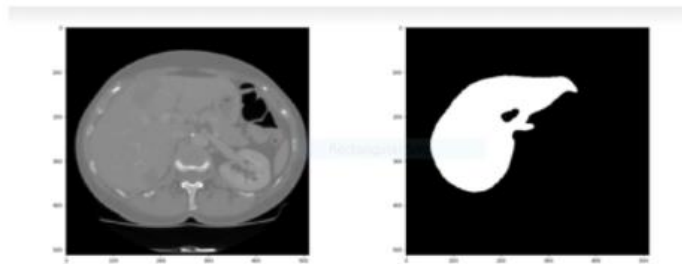


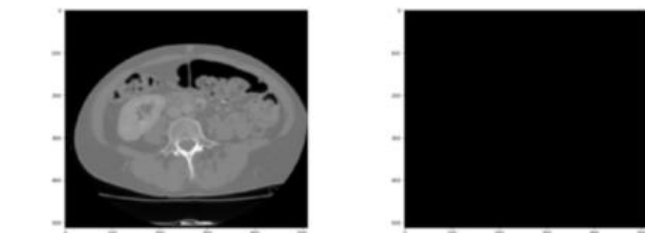
Fig 5: ResUnet Architecture.

We took the data and evaluated it on the model and the results an Accuracy of 99.8% and a Dice Coefficient (F1 Score) of 99.3%. By making use of the ResUNet model, accuracy of results is improved. From 89% in 2d-unet, it has reached to 99.8% that is the successful outcomes of the experiment as we increased the number of epochs. The value of Dice Coefficient also displayed significant positive changes that are reminder that the segmentation of liver is done properly. We use a CNN (ResUNet) for the sole purpose of Liver Segmentation. It is trained on CT scans and Liver masks to be able to detect the Region of Interest (ROI) in order to segment the liver and mask the neighboring organs as we have no interest in them.

Liver segmentation with liver:



Liver segmentation without liver:



At first, we used a U-Net to segment the tumors in the liver but got bad results so we tried using the ResUNet to segment the tumors. It is trained on CT scans of the Liver after extracting the ROI from the first CNN along with the tumors' masks., we used a U-Net to segment the tumors in the liver but got bad results so we tried using the ResUNet to segment the tumors. It is trained on CT scans of the Liver after extracting the ROI from the first CNN along with the tumors' masks.

Liver with tumor:



Liver without tumor:

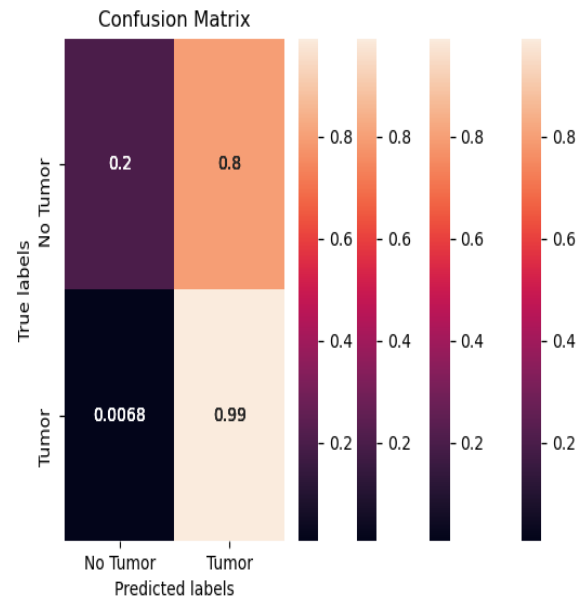


Fig 6: Confusion Matrix from the predicted value of the first slice

5. RESULTS.

After using the ResUNet model to segment the Tumors we got the following results



Figure 7: Progress of training the ResUNet model for liver segmentation on our dataset for 20 epochs.

In order to increase the insight on the presented results, Table 1 presents a comparison between the overall accuracy of the proposed method in comparison to some selected work from the literature, according to the results reported in their published papers. From our method, we have achieved considerably higher accuracy than the work in the previous papers.

Table 1: Comparison with existing study

Application	Method	Accuracy
Liver tumor candidate classification	Random Forest	90%
Automatic liver and tumor segmentation of CT and MRI	Cascaded fully convolutional neural networks (CFCNs) with dense 3D conditional random fields (CRFs)	94%
Liver tumor detection using ResUNet	ResUNet	99.2%
Liver tumor detection using 2d-UNet	2d-unet	95%

6. CONCLUSION AND FUTURE WORK

In this paper, we have proposed segmentation of liver and its lesion using different architectures of convolutional networks along with a tumor detector. The main contributions of the paper are that the ResUNet outperforms U-Net in the case of liver extraction with a very high DICE score of 0.9527 over 0.9207.

In this work we used the ResUNet model for pixel-wise automatic liver and liver tumors segmentation using CT scans. CNNs helped us achieve our goals and are one of the best techniques that can be used in the segmentation of liver tumors and should be tried with different tumors than liver tumors, also the ResUNet showed very promising results. CNNs helped us achieve our goals and are one of the best techniques that can be used in the segmentation of liver tumors and should be tried with different tumors than liver tumors, also the ResUNet showed very promising results.

By using more datasets and wide variety of pre-processing techniques, the efficiency of ResUNet model can be improved and accuracy can be increased. For the future, it can probably provide help to diagnose the small-scale liver tumor which are hard to detect with 99.9% accuracy. The value of Validation of Dice Coefficient (F1 Score) also refined that is showcasing that the experiment was performed successfully and the model is displaying great results.

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