



# MEDICAL IMAGE PROCESSING USING DEEP LEARNING

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**Abstract:** CT scan analysis is becoming increasingly important in the diagnosis and treatment of abdominal organs. Automatic organ segmentation of abdominal CT scans can help radiologists analyze scans faster and more accurately diagnose disease and injury. However, existing methods are insufficiently efficient for segmenting victims of accidents and emergency situations. We propose an efficient liver segmentation using our HFCNN (Hybridized Fully Convolutional Neural Network) and a public data set (3DIRCADB) in this paper. As a result, we segment a target liver with a Dice score of 97.22 percent.

**Index terms -** Liver Segmentation, deep learning, CT image segmentation, Wiener, HFCNN.

## I. INTRODUCTION

The liver is a wedge-shaped organ located on the right side of the upper abdomen; it is the largest gland in the body and is in charge of performing several vital functions to keep the body free of toxins and harmful substances. Computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US), Positron Emission Tomography (PET), or Single-Photon Emission Computed Tomography are Non-invasive techniques used to diagnose liver pathologies such as cirrhosis, liver cancer, and fulminant hepatic failure (SPECT). One of the benefits of CT images is that they have a higher signal-to-noise ratio, better spatial resolution, and provide more accurate anatomical information about the visualized structures; thus, diagnosticians prefer to use CT images. The segmentation of the liver from medical images is extremely difficult due to the complexity of liver shapes and variable liver sizes among patients, as well as the low contrast between the liver and surrounding organs.

The first significant process in computed tomography for liver diagnosis is liver segmentation (CT scan images). Image segmentation is the process of dividing an image into different phases while keeping track of important properties for each phase. The first significant process in computed tomography for liver diagnosis is liver segmentation (CT scan images). Image segmentation is the process of dividing an image

into different phases while keeping track of important properties for each phase. The goal of segmentation is to simplify and/or change an image's representation into something more meaningful and easier to analyze.

To evaluate the pre-processing stage of Liver abnormality analysis using Wiener filter. Using the Wiener filter, assess the pre-processing stage of Liver abnormality analysis. To remove noise and imperfection from the image. The Hybridized Fully Convolutional Neural Network has been proposed for detecting and segmenting liver. Each neural network in the system goes through a training and testing phase.

## II. SURVEY

Many semi-automatic and fully automatic approaches to improving the liver segmentation procedure have been proposed. Our work is motivated by the desire to train a high-performance DCNN model with a relatively large 3D medical dataset, which can then be used as the backbone pre-trained model to boost other tasks with insufficient training data.[1]. Due to patient privacy, CT images of anonymous patients are used during the experiment. The dataset consists of 20 torso CT images and liver masks of these images from 20 patients. The masking process was carried out by subject matter experts from the party that provided the tomography images. These masks enable the liver to be distinguished from other organs during the segmentation and training processes. The first version of the Unet framework represented flaws and the elimination of negative in various tissue structures such as the color intensity of long-distanced organ. The test data set was processed by the network with 2D image slice. The input image slice consists of either six channels of the DCE-MR phase images and three channels of DWI images or nine channels. It depended on the network. The probability output was masked by the liver segmentation, which was dilated with a  $5 \times 5$  structure element. The dilation of the liver segmentation is a safety measure to ensure that small failures in the liver segmentation would not lead to undetected liver metastases.

## III. METHODOLOGY

Medical image segmentation is an important task in both diagnosis and pre-surgery. Deep learning has recently made a significant contribution to improving the efficiency of medical image extraction. For medical image segmentation, the U-Net network has been a popular network model that has been used as a platform architecture.

### DATASET

Here 3D-IRCADb-01 dataset is used. This dataset has composed of three-dimensional CT-scans of 20 different patients. Each image has a resolution of  $512 \times 512$  width and height. The patient images are in DICOM format labeled with mask images are used as ground truth for segmentation process.

## PREPROCESSING - WIENER:

Simultaneously removes additive noise and inverts blurring. In terms of mean square error, Wiener filtering is optimal. In other words, it minimizes the overall mean square error during the inverse filtering and noise smoothing processes. Wiener filtering approximates the original image linearly. In digital hearing aids, a Wiener filter is used to suppress the noise signal that is combined with the speech. The Wiener filter is useful in noise suppression and enhancement because it estimates the relationship between the power spectra of the noise-affected noise signal and speech signal. The Wiener filter's purpose is to remove noise that has corrupted a signal. It is based on statistical analysis. Typical filters are built to achieve a specific frequency response. According to the orthogonality principle, the Wiener filter in the Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{H^*(f_1, f_2)^2 + S_{xx}(f_1, f_2) + S_{nn}(f_1, f_2)}$$

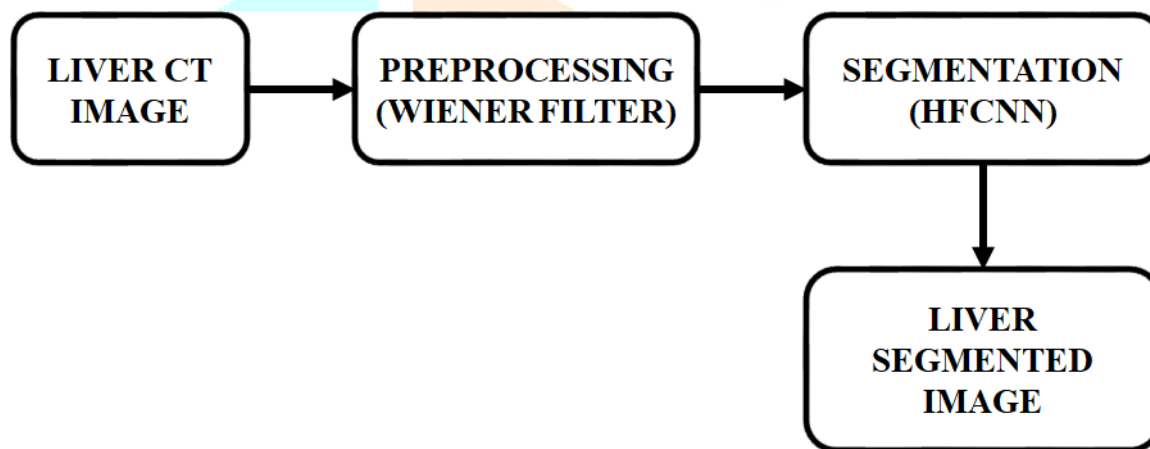
This algorithm is used to preprocess i.e., Remove the noise of the images.

## HYBRIDIZED FULLY CONVOLUTIONAL NEURAL NETWORK:

The Hybridized Fully Convolutional Neural Network has been proposed for detect and segment liver. Each neural network in the system goes through a training and testing phase. During the training phase, some methods known as data augmentation were used to improve the collected CT data. The enhanced knowledge, known as input data, is then entered into the neural network system to obtain a qualified framework. To segment the liver in this study, a fully convolutional neural network architecture was used. Recently, the fully convolutional architecture has been used in the medical sector. Fully convolutional networks that have been hybridized will take arbitrary inputs and generate the correct output with efficient inference and learning. As with the patch-based approaches, the loss function is evaluated over the entire image segmentation object with this system.

Medical image segmentation is an important task in both diagnosis and pre-surgery. Deep learning has recently made a significant contribution to improving the efficiency of medical image extraction. The work involved in this project is to develop an automatic segmentation method based on a priori knowledge of the image, such as the location and shape of the liver, for the purpose of identifying the liver in CT images. The liver can be found in the upper right quadrant of the abdomen, on the right side of the stomach, and above the intestines. It reaches all the way from the abdomen to the thorax. The liver is visible on the left side of the CT image from the observer's point of view. In order to improve the quality of digital nuclear medicine images, we created a new Wiener restoration filter implementation. The Wiener filter's optimality criterion is the minimization of the mean-square error between the object's undistorted image and the filtered

image. The object and noise power spectrums are required to construct this filter. The noise power spectrum of nuclear medicine images with count-dependent Poisson noise is shown to have a constant average magnitude equal to the total count in the image. For liver segmentation, a Hybridized Fully Convolutional Neural Network has been proposed. Each neural network in the system goes through a training and testing phase. During the training phase, some methods known as data augmentation were used to improve the collected CT data. The enhanced knowledge, known as input data, is then entered into the neural network system to obtain a qualified framework. The testing of various layers of HFCNNs in our feature extraction process has attempted to find a better feature extraction network. Several iterations were performed during the training phase of this project to achieve a better model structure. A variety of traditions have been used in the extraction process, which are well-represented in the field of computer vision extraction functions. To reduce false positives of initially identified lung nodule candidates, a 2D HFCNN-based classification system has been developed for classifying lung nodule candidates as positive lung nodules and negative non-nodules.



#### IV. RESULT

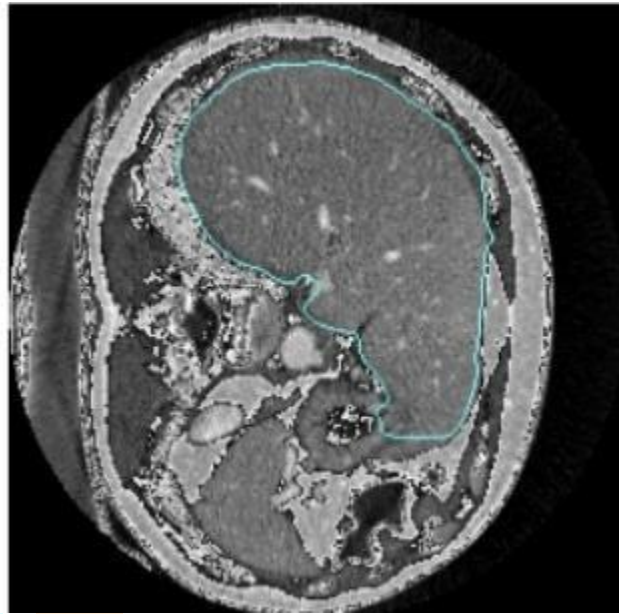
To evaluate the segmentation results, three evaluation values from all metrics were chosen: Dice's Similarity Coefficient (DSC), Volumetric Overlap Error (VOE), and Relative Volume Difference (RVD). The equations for the three metrics are written as

$$DSC(G, P) = \frac{2|G \cap P|}{|G| + |P|} = 96.38 \pm 0.06$$

$$VOE(G, P)_1 = \frac{|G \cap P|}{|G \cup P|} = 6.36 \pm 0.41$$

$$RVD(G, P) = \frac{|P| - |G|}{G} = 1.99 \pm 0.01$$

Where G is the ground truth case number and P is the positive prediction case number. A lower VOE and RVD value indicates a better segmentation result. The greater the value close to one for Dice's Similarity Coefficient, the better the result.



## V. CONCLUSION

The liver is segmented in this study using the U-Net architecture. The input liver image is pre-processed with the Wiener filter, which completely eliminates noise in the input liver image. The quality of the input liver image improves after pre-processing. The pre-processed or noise-reduced image is then segmented into multiple regions. In this work, the U-Net architecture is used for segmentation. The U-Net architecture is one of the most important and revolutionary breakthroughs in deep learning. The accuracy of medical image detection is improved by using this U-Net architecture. This algorithm produced liver volume measurements that have been 97.22 percent accurate. In this study, the segmentation accuracy is found to be very high.

## VI. REFERENCES

1. Sihong Chen, Kai Ma and Yefeng Zheng . Med3d: Transfer Learning for 3d Medical Image Analysis,2019.K.E. Sengun, Y.T. Cetin, M.S. Guzel,S.Can and E.Bostanc . Automatic Liver Segmentation from CT Images Using Deep Learning Algorithms:A Comparative Study,2019
2. S. Li, M. Dong, G. Du and X. Mu, "Attention Dense-U-Net for Automatic Breast Mass Segmentation in Digital Mammogram," in IEEE Access, vol. 7, pp. 59037- 59047, 2019.
3. Mariëlle J.A. Jansen,, Hugo J. Kuijf,, Maarten Niel,, Wouter B. Veldhuis,, Frank J. Wessels, Max Viergever,, and Josien P.W. Pluim. Liver segmentation and metastases detection in MR images using convolutional neural networks,2019.
4. S. Cai, et al., "Dense-UNet: a novel multiphoton in vivo cellular image segmentation model based on a

- convolutional neural network”, *Quantitative Imaging in Medicine and Surgery*, 10(6), 2020.
5. S. Can., “A New Segmentation Algorithm for Medical Images and Analysis Application”, MSc thesis , Ankara University, TR, 2019
  6. Zhaohan Xiong, Vadim V Fedorov, Xiaohang Fu, Elizabeth Cheng, Rob Macleod, and Jichao Zhao. Fully automatic left atrium segmentation from late gadolinium enhanced magnetic resonance imaging using a dual fully convolutional neural network. *IEEE transactions on medical imaging*, 2018.
  7. Jiawei Lai, Hongqing Zhu, Xiaofeng Ling, "Segmentation of Brain MR Images by Using Fully Convolutional Network and Gaussian Mixture Model with Spatial Constraints", *Mathematical Problems in Engineering*, vol. 2019, Article ID 4625371
  8. D. Karimi and S. E. Salcudean, "Reducing the Hausdorff Distance in Medical Image Segmentation With Convolutional Neural Networks," in *IEEE Transactions on Medical Imaging*, vol. 39, no. 2, pp. 499-513, Feb. 2020
  9. E. Vorontsov, A. Tang, C. Pal, and S. Kadoury, “Liver lesion segmentation informed by joint liver segmentation,” in *Proceedings of IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, pp. 1332–1335, 2018.
  10. Siqi Liu, Daguang Xu, S. Kevin Zhou, Olivier Pauly, Sasa Grbic, Thomas Mertelmeier, Wicklein. 3D anisotropic hybrid network: Transferring convolutional features from 2D images to 3D anisotropic volumes. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2018.

