Journal of Artificial Intelligence and Capsule Networks (ISSN: 2582-2012)
www.irojournals.com/aicn/

ResNet50-Boosted UNet for Improved Liver Segmentation Accuracy

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Abstract

Segmentation of the liver from abdominal CT images is difficult due to changes in form, density, and the presence of malignancies. This research describes a novel strategy to improve segmentation accuracy that uses UNet as a foundation architecture and ResNet50 as a backbone architecture. This integrated design automates feature selection and spatial awareness, overcoming limitations in previous models. Experimental evaluations using the LiTS dataset show higher performance. Specifically, using the LiTS dataset, our algorithm achieves a remarkable foreground accuracy of 99.81% in liver segmentation. These results outperform existing approaches, demonstrating UNet and ResNet50's potential as valuable tools for precise liver segmentation in clinical situations. The suggested system shows promise for application in diverse medical imaging tasks other than liver segmentation, demonstrating its versatility and effectiveness in enhancing machine-assisted medical diagnostics and decision-making processes.

Keywords: Liver Segmentation, Deep Learning, UNet, LiTS, CT Scan.

DOI: https://doi.org/10.36548/jaicn.2024.1.006
Received: 10.01.2024, received in revised form: 14.02.2024, accepted: 02.03.2024, published: 12.03.2024

1. Introduction

Liver segmentation holds paramount importance in facilitating precise diagnoses and treatment for diseases caused in. The advent of artificial intelligence (AI) has revolutionized this domain, offering automated solutions that augment clinicians' efforts. Accurate organ contouring is becoming increasingly important, especially for organs at risk (OARs) like the liver, because to the development of sophisticated radiation treatments like “intensity-modulated radiotherapy (IMRT) and volumetric modulated arc therapy (VMAT)”. The tedious, inconsistent, and time-consuming nature of manual delineation of these structures highlights the need for effective computational techniques. Traditional segmentation methods, although valuable, often struggle to handle the complexities of liver anatomy and pathology found in computed tomography (CT) scans. The diverse range of liver conditions, such as tumor, cirrhosis, cysts, fatty liver, and fibrosis, presents formidable challenges to conventional algorithms. Despite the progress made in liver segmentation research, the quest for robust, automated solutions persists. The convergence of deep learning and medical imaging provides a promising avenue for addressing these challenges. DCNNs, in particular, have demonstrated remarkable prowess in end-to-end liver segmentation, leveraging their ability to discern intricate semantic features from image data. Yet, the translation of these advancements from research to clinical practice faces hurdles, including the utilization of volumetric CT data and the incorporation of spatial information for accurate segmentation.

A novel architecture integrating UNet and ResNet50 is proposed, integrating elements of UNet and ResNet50, the model is tailored for high-accuracy liver segmentation on abdominal CT images. Our approach overcomes the limitations in existing methods by harnessing the complementary strengths of different network architectures. Through the use of advanced preprocessing techniques, optimization algorithms, and loss functions, we strive to develop a robust segmentation system capable of accurately delineating liver regions. Through rigorous experimentation and comparison with existing techniques in use, we aim to establish the efficacy and practical utility of our proposed framework, thereby advancing the frontier of liver segmentation in medical imaging.

2. Related Work

It is difficult to segment liver tumor and liver. Multiple automated methods are developed for the accurate as well as fast extraction of the hepatic lesions as well as liver from CT volumes. Several techniques that have been created thus far rely on texture. [1]. Since each patient's lesions vary in size, form, and location, segmenting liver tumor would be more challenging than segmenting livers [5] [3].

Primary obstacle in liver segmentation is the poor contrast between the liver and the surrounding organs [4]. A residual path is used in the suggested network to prevent the feature map with low-resolution data duplication. However, the suggested network, in contrast to the earlier study from [2], the residual path is placed on the right next to pooling. Liver and tumor segmentation methods involve combining high-resolution edge information through skip connections with extra convolution layers, categorized as manual, semi-automatic, or automatic extraction approaches in the literature. [6].

The manual segmentation process takes a long time and is dependent on human competence. Since computers were included in the inquiry responsibilities, this has hardly been applied in real-world applications. Using automated computer methods, semi-automatic segmentation also needs human implementation. Although it relies on the computer's performance, this strategy saves time. A fully automated extraction system would be highly desired to lessen the workload for medical personnel. Thus, the ultimate goal for researchers is automatic segmentation [7].

A completely automatic technique for identifying the liver region from CT images was created in 2020 by Thi et al. [8]. It was built on a “Multiple Filter UNet, or MFUNet. The author in [9] reports that UNet was enhanced with an attention gate. This technique first mixes data from the increasing path and skip connection.

After using the ReLu activation function on the combined data, a linear transformation is carried out. At last, the sigmoid function is applied to it. Attention coefficients are employed here to suppress irrelevant features. A hybrid network known as SWTR-UNet was created in 2022 by Hille et al. [10]. Christ et al. developed a model for autonomously segmenting lesions and the liver in abdominal CT images. [23].

Sun et al. introduced the multi-channel FCN model for liver lesion segmentation, tested on 3Dircadb and JDRD datasets [13]. Bi et al. enhanced segmentation using ResNet50, maintaining accuracy with residual skip connections [14]. Their model, assessed on the LiTS dataset, achieved accurate boundary delineation. Contrast-enhanced CT scans are vital for liver cancer detection due to high sensitivity and specificity. Rex and Cantlie proposed hemilivers and serge for manual liver segmentation [15].

3. Proposed Work

The UNet [21] (Figure 2) + ResNet50 [22] (Figure 3) model is used to train on abdominal grayscale CT scans, with a variety of training options selected. Following that, segmentation performance is evaluated by calculating the foreground accuracy parameter after testing the model on a set of images not included in the training dataset. Figure 1 provides an outline of the proposed work.

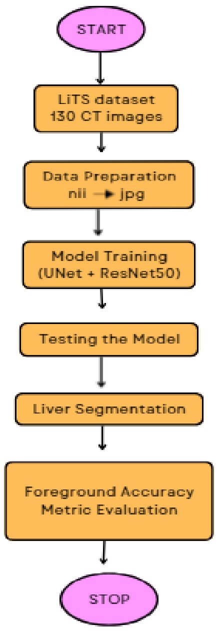

Figure 1. Flowchart.

3.1 Dataset

LiTS17 [23] is a baseline for segmenting liver tumor. Numerous clinical locations worldwide provide the segments and data. The dataset contains a total of 200 CT scans, divided into a training set and a test set.

- Training Set: 130 CT scans
- Test Set: 70 CT scans

The LiTS17 dataset's data comes from several clinical sites across the globe. For research purposes, these locations provide CT scans and the associated tumor segmentation data. The goal of the dataset is to provide a standard against which liver tumor segmentation algorithms can be measured. It gives scientists a common set of data to work with when creating and contrasting automated tumor segmentation techniques for CT scans. Researchers may create and assess liver tumor segmentation algorithms using the LiTS17 dataset, advancing the field of medical imaging and clinical practice.

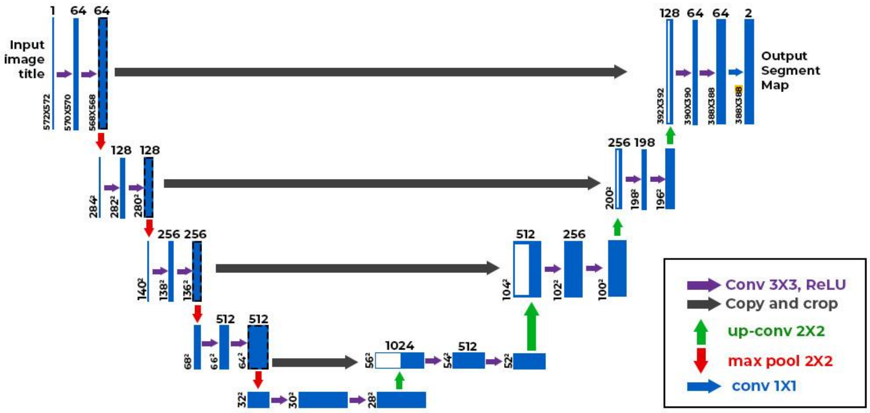

Figure 2. UNet Architecture. [21]

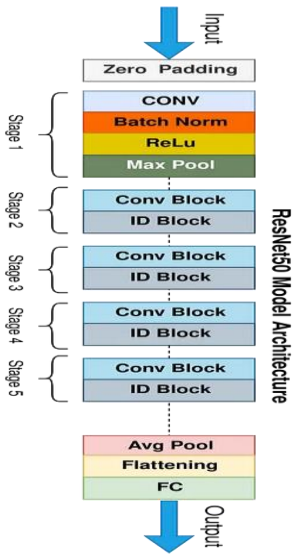

Figure 3. ResNet50 Architecture. [25]

3.2 Data Preparation

The CT image from the LiTS [23] dataset is associated with its relevant label, and the CT scan images are windowed using defined width and level parameters for various organs, as described in Fastai's medical imaging documentation. This windowing technique improves the visibility of anatomical structures in CT scans. Furthermore, histogram scaling is used to improve contrast and emphasize key characteristics in the liver region. The processed images can be used as input data in the training phase of a liver segmentation algorithm. These pre-processed pictures are combined with their corresponding ground truth masks as shown in Figure 4 to train a neural network, allowing for the establishment of an accurate and resilient liver segmentation model.

Figure 4. Data Preparation from Raw CT Images.

3.3 Model Training

The network uses a hybrid design, integrating UNet and ResNet50 layers, to accomplish precise liver segmentation. Its structural composition consists of an encoder segment on the left and a symmetrical decoder component on the right, which constitute the distinctive 'U' shape of UNet. The encoder, along with ResNet50 layers, excels in capturing detailed characteristics and patterns in input data, while the decoder expertly reconstructs the segmented output. Leveraging ResNet50's deep residual learning skills improves the network's ability to deal with complex connections and gradients during training, leading to more effective and precise liver segmentation. The approach outlined in this study mirrors the methodology proposed by [24], wherein a similar hybrid architecture combining UNet and ResNet50 was utilized for liver segmentation.

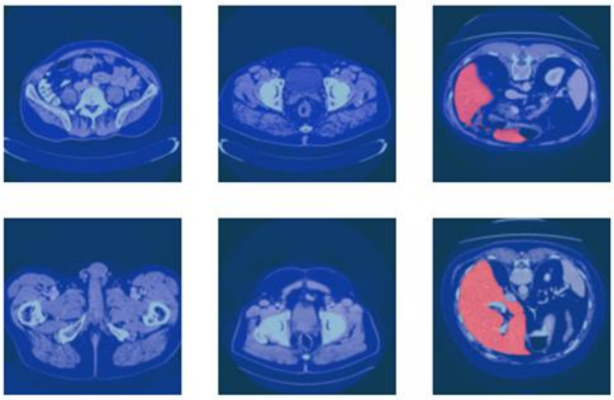

Figure 5. Training CT Images with Various Orientations of the Liver.

During training, the network employs the Cross-Entropy Loss, Flat loss function, indicating its application to a multi-class segmentation task. This comprehensive framework (UNet + ResNet50) establishes a robust foundation for training the medical images as shown in Figure 5, specifically designed to achieve accurate liver segmentation.

3.4 Testing the Model

The processed CT scan data that were acquired using the previously outlined processes are used in the next stage of the workflow to evaluate the effectiveness of the trained U-Net model using a ResNet50 backbone. The model uses these processed samples as a representative input during the testing stage. These samples can be used to assess the model's performance in precisely segmenting the liver and making efficient use of the combined UNet and ResNet50 architecture. This testing procedure is essential for confirming the model's functionality and effectiveness in precisely identifying liver structures in medical imaging. Figure 6 shows the expected target segmentation to be performed on the CT image and its corresponding model output segmentation.

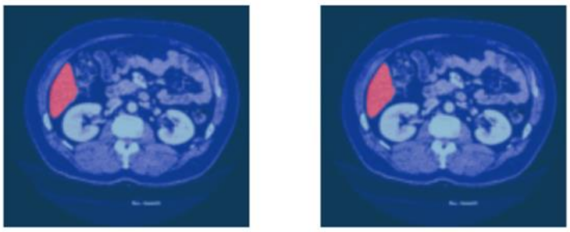

Figure 6. Target vs Predicted.

4. Experiment and Results

4.1 Evaluation Metrics

In the assessment of segmentation performance, the model's binary segmented output, representing both the liver, is compared to a ground truth mask. The evaluation metric employed for this analysis is foreground accuracy.

4.1.1 Foreground Accuracy

In segmentation, foreground accuracy is a measure of how well a model locates and demarcates the item or region of interest in an image. A picture is segmented into multiple regions for segmentation tasks, and foreground accuracy evaluates the ability of the model to capture the pixels that correspond to the target object, which might be an organ or a particular structure.

$$Foreground\ Accuracy = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Here:

True Positives (TP) are the number of pixels correctly identified as foreground by both the model and the ground truth.

False Negatives (FN) are the number of pixels that are part of the foreground in the ground truth but are incorrectly classified as background by the model.

4.2 Computing Environment

The developed technique was trained using a Kaggle notebook equipped with a GPU P100, providing significant computational advantages. The utilization of GPU acceleration enhances the training speed and allows for more complex model architectures, resulting in improved segmentation performance. The dataset is partitioned into training and testing sets using an 85% to 15% ratio**.**

ISSN: 2582-2012

4.3 Results of Liver Segmentation

Foreground accuracy is used to evaluate liver segmentation, and our model which combines UNet and ResNet50, achieved a remarkable foreground accuracy of 99.81% on the LiTS dataset. This parameter demonstrates the model's efficacy in medical image segmentation tasks by signifying its high precision and accuracy in accurately detecting and defining the liver region in medical pictures.

The specific details regarding the relationship between epochs and loss and epochs and accuracy are visually represented in Figure 7 and Figure 8, where each epoch's corresponding loss and accuracy values are graphically depicted. These graphs serve as a valuable tool for assessing the model's convergence and performance optimization over the course of training.

Table 1. Accuracy and Loss Values for 4 Epochs on LiTS Dataset

Epoch	Loss	Accuracy
0	0.021107	0.992469
1	0.007713	0.997361
2	0.015072	0.997751
3	0.013335	0.998143
4	0.012334	0.998160

The values in Table 1 provide a detailed snapshot of the model's performance across the first four epochs of training on the LiTS dataset. As training progresses, the validation loss consistently decreases from 0.021107 to 0.012334, indicating the model's ability to minimize errors and converge toward optimal parameters. Simultaneously, the custom foreground accuracy steadily increases from 0.992469 to 0.998160, demonstrating the model's continual improvement in accurately identifying and delineating liver structures in medical images.

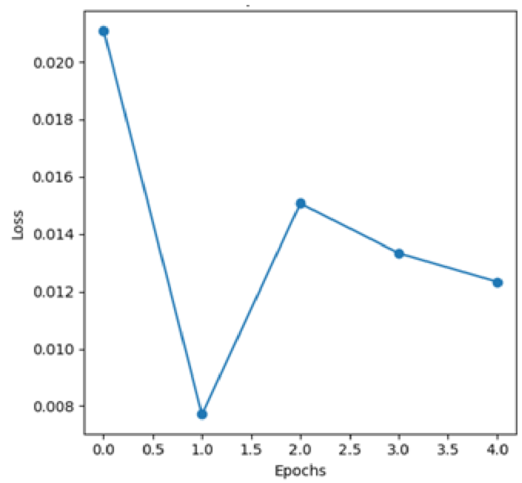

Figure 7. Epochs vs Loss.

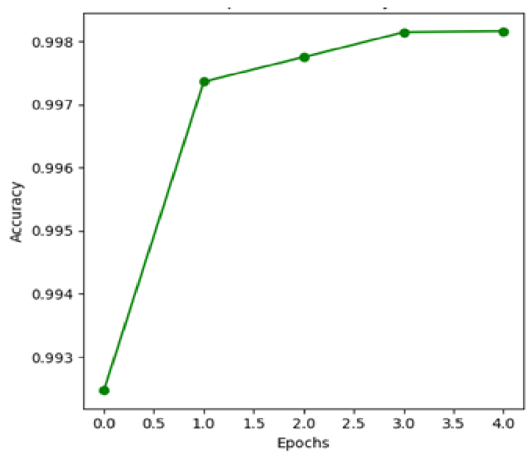

Figure 8. Epochs vs Accuracy.

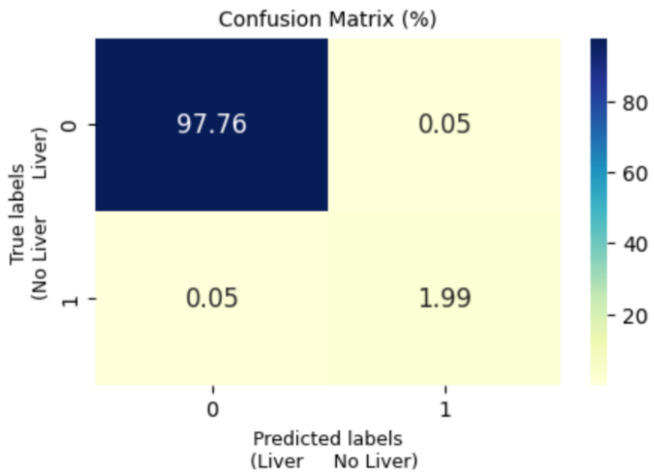

Figure 9. Confusion Matrix.

Figure 9 Shows the confusion matrix obtained for the liver segmentation using the UNet and ResNet50 Model.

Table 2. Comparative Analysis of Model Performance

Authors	Epoch	Accuracy
[19]	20	0.9923
[20]	150	0.93
Proposed	4	0.9981

5. Conclusion

In this research the proposed method focuses on addressing the challenging task of liver segmentation using advanced deep learning algorithms applied to the LiTS dataset. Our proposed model, a synergistic blend of UNet and ResNet50, has demonstrated superior performance compared to existing deep learning models. The model achieved an outstanding foreground accuracy of 99.81% on the LiTS dataset with a resolution of 128 × 128, surpassing the capabilities of other approaches. The comparative analysis, as illustrated in Table 2: Comparative Analysis of Model Performance, underscores the effectiveness of our model against previously published methods.

Looking forward, potential avenues for future research include extending the analysis to include volumetric assessments not only for the liver but also for liver tumors and fatty liver in CT images. Additionally, exploring additional evaluation parameters beyond foreground accuracy could provide a more comprehensive understanding of the segmentation process. The adaptability of automatic segmentation techniques to different organ datasets could open up broader applications in the field of medical image analysis.

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