Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Liver Tumour Semantic Segmentation Using Segan

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Abstract: Liver tumor detection and segmentation are critical tasks in medical imaging, aiding in early diagnosis and treatment planning. Convolutional neural networks (CNNs) have demonstrated significant success in the examination of medical images, particularly in semantic segmentation. In this study, we proposed a system called Semantic Segmentation with Adversarial Network (SegAN) for the accurate and efficient semantic segmentation of liver tumors from medical images. SegAN combines the power of generative adversarial networks (GANs) with CNN to address the challenges of limited annotated data and class imbalance in liver tumor segmentation (LiTS). The SegAN architecture have a generator network that produces high-quality tumor segmentation masks and a discriminator network that enforces segmentation mask realism. Our method leverages a collection of medical images to train the network and adapts GAN-based adversarial training to enhance segmentation accuracy. We evaluate SegAN on a diverse data set of liver tumor images and contrast it to other state-of-the-art segmentation methods. The output demonstrate that SegAN achieves superior accuracy and robustness, outperforming existing techniques in LiTS tasks.

Keywords*:* Convolutional Neural Networks, Generative Adversarial Networks, Semantic Segmentation with Adversarial Network, Semantic Segmentation, Liver tumor segmentation.

1. Introduction

In medical industry examination of medical images is a big issue. In medical pictures, segmentation of image is the process of locating and defining the borders of items like organs or aberrant areas like tumors. The development of exact and dependable automatic segmentation methods is necessary for applications in research and medicine since the manual annotation of these pictures is a laborious and subjective procedure. [2]

The topic of discussion turns to liver cancer, which is noted as the fourth-highest malignancy in terms of death and the sixth most frequent disease worldwide. In 2018, there were over 782,000 liver cancer fatalities, or 85 cases per million people, and about 841,000 new instances of liver cancer, or 93 cases per million people. Considering these figures, it becomes clear that sophisticated medical image processing methods are required, especially for the division of lesions and the liver.[1]

Finding the voxels, or volumetric pixels, that represent the liver and lesion areas in medical pictures is the major task of LiTS. The objective is to provide efficient techniques for automated segmentation, as this will help with later tasks including form analysis, volume change detection, and accurate radiation therapy treatment planning. [1][2]

Using a novel design, Generative Adversarial Networks (GANs) train a discriminator (also known as a critic) and a generator neural network simultaneously through adversarial training. Critic calculate the veracity of both created and actual data, whereas the generator creates synthetic data. The Critic's goal is to enhance its ability to figure out between original and synthetic data, while the generator aims to generate data that is indistinguishable to actual data.[6] Within this framework, fully connected neural networks (FCNs) are frequently employed as the discriminator and generator, resulting in an integrated architecture. The generator is prompted to improve its output in order to successfully trick the discriminator, which is a FCN that assesses the veracity of created data through linked layers. [11]

In medical imaging, LiTS is the process of locating and defining tumors for the purposes of diagnosis and therapy. SegAN and FCN combination technique works well in this situation. The main segmentation model is FCN, which processes medical pictures using convolutional layers. Next, SegAN is used to improve the first segmentation by using adversarial training to improve semantic details. The input data for the workflow consists of medical photos showing liver cancers. After applying FCN for the first segmentation, SegAN is used to further hone the outcomes. Using labeled data, the entire system is supervisedly trained to optimize the FCN and SegAN components for LiTS according to ground truth. It is imperative to recognize that the achievement. [2][11]

FCNs is used for initial segmentation in the Semantic Segmentation with Adversarial Network (SegAN) and FCN combined approach for liver tumor segmentation. FCN uses its convolutional layers to capture both local and global features, allowing an understanding of short-range relationships among neighboring pixels. As a generative adversarial network, SegAN leverages adversarial training to improve semantic content by emphasizing abstract features and long- range interactions. FCN performs the first segmentation during supervised training, taking into account local pixel associations, while SegAN refines the segmentation maps to offer better semantic details and overall coherence. generator (FCN) that creates segmentation maps that are identical to the ground truth is used in SegAN's adversarial training, forcing the network to learn long-range linkages. SegAN refines the maps produced by FCN through an iterative process, creating a feedback loop that captures both short- and long-range associations. Local pixel relationships (FCN) and improved semantic details (SegAN) are integrated with optimization to minimize discrepancies between generated maps and ground truth, resulting in accurate liver tumor delineation. By combining these two methods, liver tumor segmentation becomes more precise as complicated structures in medical imaging are better understood. [2][6][11]

2. Literature Survey

[1] S.-T. Tran, (2021), this paper suggests a novel U-Net model architecture called Un-Net. Building on the classic U- Net network design, an n-fold network design is called Un-Net. Using two datasets, LiTS and 3DIRCADb, the authors assessed the performance of their Un-Net. Un-Net obtained Dice similarity coefficients (DSCs) for liver segmentation of 96.38% on LiTS and 96.45% on 3DIRCADb. Additionally, the Un-Net obtained DSCs for tumor segmentation of 73.69% on LiTS and 73.34% on 3DIRCADb dataset. These outcomes match those of the top-performing techniques on these datasets. In conclusion, on two publicly available datasets, the Un-Net produced state-of-the-art results. Future developments are anticipated for the Un-Net, a potential new technique for segmenting liver and liver tumors.

[2] Xue, Y., Xu, T., (2018). The paper suggests a brand-new adversarial neural network for semantic segmentation termed SegAN, which operates end-to-end. The training process for SegAN, which draws inspiration from traditional generative adversarial networks (GANs). The BRATS 2013 and BRATS 2015 public datasets were used by the authors to assess the performance of their SegAN. On both datasets,SegAN performed at the cutting edge. For BRATS 2013, SegAN received dice scores of 0.937 on whole tumour, 0.878 on tumour core, and 0.790 on GD-enhanced tumour. For BRATS 2015, SegAN obtained dice scores of 0.941 on tumor core, 0.886 on entire tumor, and 0.800 for GD-enhanced tumor core segmentation. In conclusion, the suggested technique is a fresh and intriguing way for semantic segmentation, and more work on it is probably in store.

[3] T. Fan, (2020), This paper introduces Multi-scale Attention Network (MA-Net) for LiTS. LiTS dataset was used to assess the MA-Net. For LiTS, the MA-Net obtained Dice similarity coefficients (DSCs) of 0.960 ± 0.03 and 0.749 ± 0.08, respectively. These outcomes are in line with those of the top-performing techniques on the LiTS dataset.

[4] T.Lei,(2022). This paper introduces (DefED-Net) a Deformable Encoder-Decoder Network for accurate LiTS. The author uses LiTS and 3DIRCADb two publicly accessible datasets to assess DefED-Net. It performs remarkably well on both datasets for LiTS in terms of DSC. Conclusion, DefED-Net shows promise as a method for medical image division of tumors and the liver. It offers cutting-edge performance thanks to its creative architecture, attention-guided deformation, and residual refinement. * More studies on generalizability

and computing efficiency may open the door to DefED-Net's widespread use in clinical applications.

[5] Almotairi S, (2020). This paper suggests a brand-new technology called SegNet for image segmentation. SegNet is an image segmentation technique that uses a deep convolutional encoder-decoder architecture. Many picture segmentation tasks, such as instance segmentation, and object recognition, have demonstrated the efficacy of SegNet. Many other types of things, such as vehicles, pedestrians, and buildings, have been segmented using it.

Conclusion, SegNet is a robust and adaptable picture segmentation system. It works well for real-time applications and has demonstrated efficacy in a range of activities. For many different kinds of computer vision applications, SegNet is a useful tool.

[6] Wei X, (2021) This paper introduces an improved GAN structure for studying segmentation of liver images. Our suggested architecture consists of a discriminator with a patch-level attention mechanism and a generator based on k- means clustering. Realistic aspect ratios for liver pictures are produced using the k-means clustering-based generator, which is crucial for increasing segmentation accuracy. The discriminator's patch-level attention technique is intended to concentrate on the most discriminative patches in the picture, which can improve the complete performance of the discriminator. The introduced architecture is very efficient for different types of medical image segmentation, like tumor segmentation and kidney segmentation and many more.

[7] Sabir, M. W, (2022). In this paper we proposed a system called ResUNet. A U-Net design enhancement that includes residual connections is called ResUNet. The sequence of convolutional layers in the encoder gradually reduces the spatial resolution of the input picture.The decoder is made up of many upsampling stages that raise the output image’s spatial resolution gradually. For the purpose of segmenting images, the network may learn long-range dependencies in the input picture thanks to the skip connections.

For biomedical image segmentation, the ResUNet architecture offers a strong and adaptable design. Given its shown efficacy across a range of applications.

[8] Chen, L. (2019). An adversarial densely connected network (ADCN) for LiTS from medical pictures has been suggested in this research. The multi-plane integrated fully convolutional network (MPNet) for liver segmentation and the deep fully convolutional neural network (DC-FCN) for tumor segmentation comprise the two main components of the ADCN. The adversarial training technique is used to improve the performance of the DC-FCN.

The ADCN was evaluated using the LiTS Challenge dataset. The results showed that, with an average Dice score of 68.4%, the ADCN beat the state-of-the-art in tumor segmentation. The ADCN likewise functioned effectively in terms of other parameters like ASD, MSD, VOE, and RVD.

[9] The new CNN architecture that the authors suggest is made especially for “Brain tumor segmentation (BTS) with Deep Neural Networks for examination of medical images”. Their approach is far quicker than existing approaches while still achieving competitive performance. All things considered, the paper offers a novel and promising method for BTS via deep convolutional neural networks. The suggested approach is much quicker than existing approaches while still achieving competitive performance. It is therefore a tool with great promise for therapeutic applications.

[10] Q. Hu et al., (2023) In order to segment liver tumors in CT images without requiring manual annotation, a unique method is presented in this work. With a range of sizes, textures, and forms, the authors’ synthetic tumor generator can produce realistic-looking tumors. After that, they used these artificial tumors to build a deep learning model, which they subsequently assessed on actual cancers. The outcomes demonstrated that a model trained on artificial tumors could perform on par with a model trained on actual tumors that had been manually annotated. This method have created a new field of study and development by enabling the training of deep learning models on artificial tumors. With this method, liver tumor segmentation could become more precise, efficient, and economical.

[11] This work explores an "Automatic liver tumor segmentation technique in CT images" by utilizing a mix of object- based postprocessing and FCNs. This work presents a cascaded strategy that combines a random forest classifier for postprocessing with an FCN akin to U-net for initial tumor segmentation. The goal of the random forest postprocessing stage is to lower the no. of false positives the FCN produces. The tumor's form characteristics, the distance between the tumor and the liver border, and other manually constructed variables are used by the random forest to differentiate between real and erroneous positive findings. In conclusion, this technique strikes a compromise between segmentation accuracy and a decrease in false positives. Alternative postprocessing methods, including multi-view neural networks, may be explored in future research.

[12] For the purpose of detecting and treating liver cancer, computer-assisted diagnostic (CAD) systems depend heavily on liver segmentation. For these purposes, it is crucial to accurately segment the liver tumors, and vasculature using medical images. The potential for advancement in computer-assisted detection/diagnosis (CAD) systems for liver cancers is also examined by the writers. In general, automatic liver segmentation techniques outperform automatic liver tumor segmentation techniques. These techniques may have limitations with regard to their automated and semi- automatic approaches.

[13] The research presents a "Liver Segmentation in CT Images using 3-D to 2- D FCN approach for autonomous LiTS in abdominal medical images. The goal of this strategy is to overcome the drawbacks of conventional approaches. The suggested technique uses a 3D–2D FCN architecture to extract 3D spatial data from the CT images that were used as input. The 3D surface and form of the liver are encoded at the 3D encoding stage by using 3D kernels to learn discriminative feature maps. This is very useful for precise segmentation—particularly for slices with incomplete liver information. 2D kernels and deconvolutional layers are used in the decoding stage to minimize memory use and generate the middle slice's final segmentation mask.

[14] A "DeepLab" system for semantic picture segmentation is proposed in this work. The system uses a number of strategies to attain cutting-edge results on difficult datasets. The efficacy of atrous convolution, ASPP, and fully linked CRFs for semantic segmentation is demonstrated by the DeepLab system's state-of-the-art performance on many benchmarks. The benefits of DeepLab, such as its simplicity, speed, and accuracy since it relies on well-known modules like CNNs and CRFs, are also highlighted in the research.

[15] Self-Attention Generative Adversarial Networks (SAGANs), a unique generative adversarial network (GAN) architecture, is proposed in this research. By including a self-attention mechanism, SAGANs tackle the problem of representing long-range relationships in visuals. SAGANs include a self-attention module that allows the network to attend to features from all picture areas in order to overcome this constraint. As a result, the generator may generate images that are more realistic and cohesive by learning the links between far-off areas of the image.

Overall, the paper indicates that SAGANs present a potential method for picture creation problems requiring modeling long-range relationships because of its spectrum normalization and self-attention mechanism.

[16] The strategy for LiTS in CT images that is proposed in this study combines many methods. These methods include an active contour model (ACM), a 3D fractal residual network (FRN), and multi-scale candidate generation. The suggested approach can handle the difficulties associated with liver tumor segmentation, such as the variable in tumor size, form, and location, thanks to the integration of these techniques: MCG, 3D FRN, and ACM. The MCG phase makes sure that pertinent tumor data is recorded in the potential locations, and the 3D FRN efficiently categorizes these regions. Lastly, for increased accuracy, the ACM refines the segmentation boundaries. This approach's efficiency in comparison to current liver tumor segmentation methods requires more investigation.

[17] The research presents a unique deep learning-based level-set methodology for LiTS in medical images. The technique uses a cascaded approach, segmenting the liver utilizing a 2D U-net and a 3D FCN in a coarse-to-fine segmentation process. Tumor segmentation is then fine-tuned using a level-set technique with an improved item indication function. Fuzzy c-means clustering data is used into the level-set approach to enhance segmentation accuracy. In general, the suggested approach aims to obtain accurate LiTS in CT images by utilizing the capabilities of deep learning for initial segmentation and level-sets for refining.

[18] In this study we provided "Cross-Modality Guided Contrast Enhancement for Improved LiTS" LiTS and Contrast Enhancement Challenges: For the purpose of prognosis and treatment planning, liver tumors on computed tomography (CT) images must be accurately segmented. However, segmentation is difficult with low-contrast CT images. A preprocessing technique called contrast enhancement (CE) is applied to medical pictures to make structures more visible. Conventional CE techniques frequently have flaws including uneven contrast distribution and over- enhancement. Cross-Modality Guided Contrast Enhancement. The authors provide Optimised Guided Contrast Enhancement (OPTGCE), a unique approach to CE that makes use of cross-modal information. To improve the contrast of CT pictures, OPTGCE makes use of MRI images, which offer superior contrast for liver tissue. This method incorporates a quality control mechanism to maintain structural information in the CT image during enhancement, hence addressing the shortcomings of conventional CE approaches.

[19] The study suggests a unique approach that makes use of an Efficient U-Net (ELU-Net) architecture for automated LiTS and BTS in medical pictures. The BraTS 2018 challenge dataset for brain tumor segmentation and the ISBI LiTS 2017 challenge dataset for liver tumor segmentation are two publically accessible datasets that the authors use to assess ELU-Net. The findings show that ELU-Net outperforms other cutting-edge techniques in terms of performance while requiring a notably smaller number of parameters, which makes it more suitable for use in clinical settings. According to the study, ELU-Net presents a viable method for automatically segmenting medical images, especially those pertaining to brain and liver malignancies. It is a good substitute for more intricate U-Net based techniques due to its lightweight design and effective architecture with deep skip connections.

[20] The spaper suggests a unique method for automatically LiTS in CT volumes by utilizing the AHCNet deep learning architecture. Overall, the suggested AHCNet architecture shows encouraging potential for automated LiTS in CT images thanks to its AHCBlocks, cascaded network design, and customized loss functions. The technique makes use of attention processes to concentrate on important information for precise segmentation and deep learning to automatically extract pertinent characteristics.

3. Methodology

SegAN is employed in the proposed methodology for LiTS from CT. As illustrated in Fig 1, SegAN

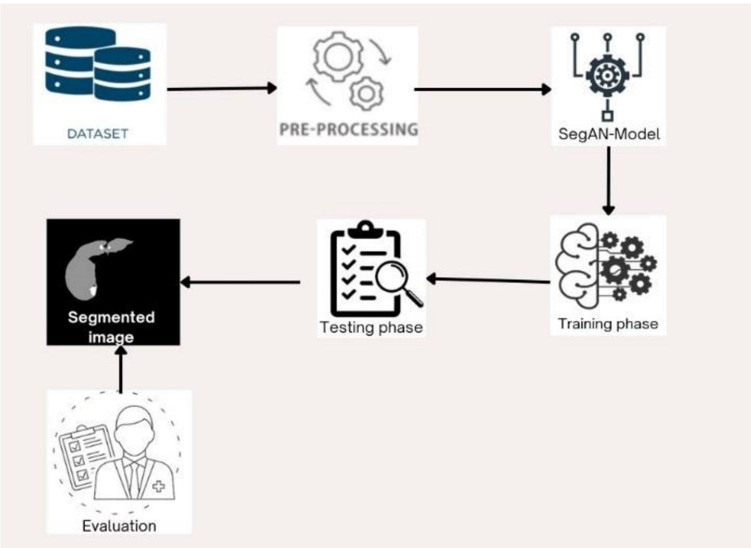


Fig.1.Architecture for proposed methodology

consist of segmentor, critic. Segmentor as S and Critic as C make up the SegAN. A probability label map is produced from input pictures by the S, a fully convolutional encoder-decoder network. The critic network receives two inputs concealed by S’s predicted images and actual images hidden by ground truth images. The S and C networks are trained in an adversarial fashion, with S trying to reduce our suggested Dice-scale loss and C trying to increase the Dice-scale function.

3.1 Dataset

Research on liver tumor segmentation frequently uses medical imaging datasets using a variety of modalities, including MRI and CT scans. These datasets are essential for machine learning model training, validation, and testing, such as generative adversarial networks for liver tumor segmentation or semantic segmentation.

This study uses the dataset that was taken from the "LiTS Challenge dataset," which is mostly utilized for liver tumor segmentation. The MICCAI 2017 conference featured the introduction of the LiTS dataset. The liver's three- dimensional contrast-enhanced CT scans are included in the dataset.

The LiTS benchmark dataset contains 201 computed tomography images of the abdomen, of which 194 CT scans contain lesions. One such CT scan is shown in figure 2.

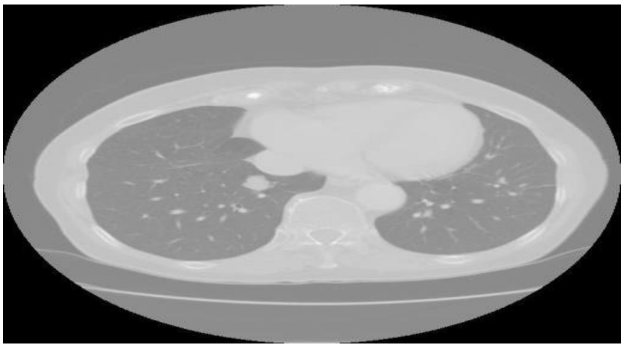
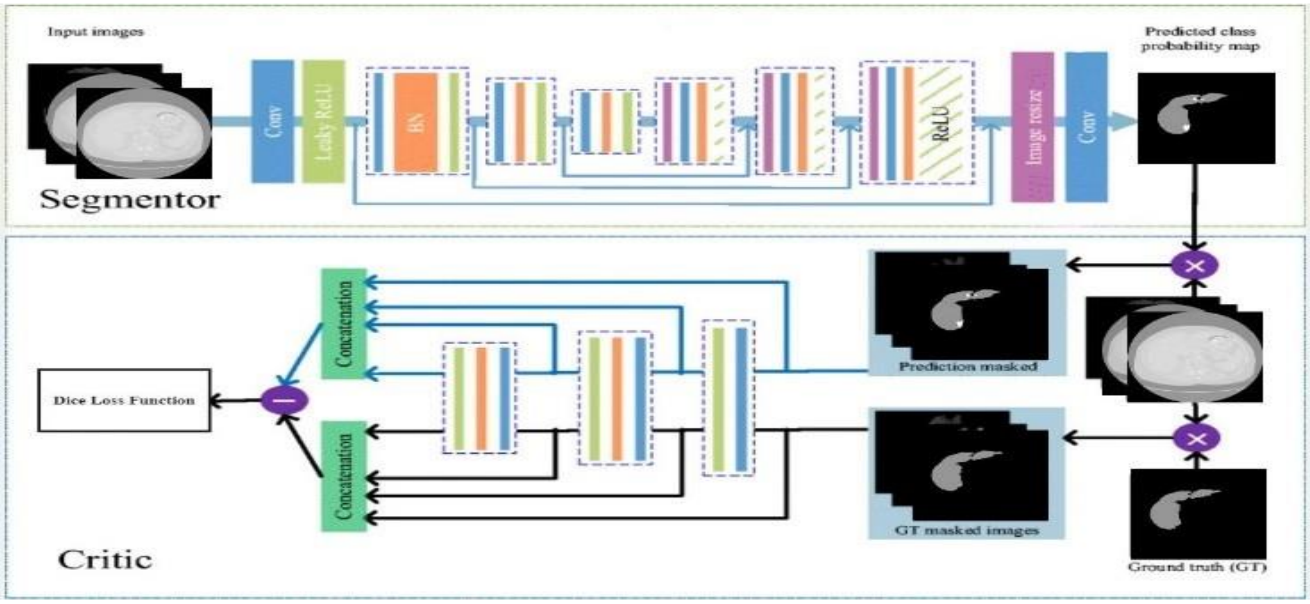


Fig 2: Sample image from the dataset

3.2. SegAN Architecture

As shown in Figure 3, the SegAN model have two components which includes: Segmentor and Critic



.Fig 3: Working of SegAN

Segmentor: S network generate predicted segmented image of liver and tumor using convolutional layer, Batch normalization layer, Leaky ReLU and image resizing layer. It try to minimize discrepancies between generated maps and ground truth.

Critic: There is structural similarity between the decoder in S and the critic C. The process of obtaining hierarchical characteristics from several layers of C yields the Dice loss function.

C network compares the predicted images generated by S network with Ground Truth images and critisize the segmentor.

Convolutional operation

The convolutional layer, a CNN's primary structural element, is where most of the processing occurs. Convolutional operation requires feature map, filter, and input data are required. An image's RGB values correspond to the input's three dimensions (height, width, and depth). In addition, we have a feature detector, also known as a kernel or filter, which looks for the feature in the image by scanning its receptive fields. We call this process a convolution.

A subset of the image is represented by a 2-D array of values that serves as the feature detector. The size of the receptive field is normally 3X3 matrix, although it may be altered; the filter size determines the size. The dot product between the input pixels and the filter is calculated after the filter has been applied to a section of the picture. After that, an output array for this dot product is provided. After the kernel has scanned the entire image, the filter advances and recedes by one step. Convoluted features, also called feature maps or activation maps, are produced by the input and filter's series of dot products. The neural network needs to have three hyperparameters that control the output's volume size configured before it can start training. Among them are:

1. Number of filters: The output's depth is impacted by the "number of filters." For instance, obtaining three separate feature maps with three different filters would result in a depth of three.

2. Stride: Striding involves skipping certain areas as the kernel slides over the input, such as skipping every 2 or 3 pixels. This approach reduces spatial resolution, enhancing the computational efficiency of the network. Our output picture dimension for fill p, filter size f*f, input image matrix of size n*n, and step's' will be:

[{(n+2p-f+1)/s} +1] * [{(n+2p-f+1)/s} +1]

3. Padding: Padding is simply adding of fake pixels to the borders of the image pixel matrix. This is done because, although our original picture is truly decreased each time the size of the original image is lowered following the convolutional operation, we don't want the image to be reduced repeatedly.

Another problem by performing convolution is from the fact that as the kernel traverses the original images, it makes fewer contacts with the image edges and more with the central regions. Additionally, there is overlapping in the middle. Consequently, the corner elements and border of any image are underutilized in the output. To address this concern, the padding concept is used. So, if the n*n image matrix is convolved with the f*f matrix with padding p, then the size of the output image will be:

(n + 2p – f + 1) * (n + 2p – f + 1)

After every convolution operation, a CNN adds nonlinearity to the model by adjusting the feature map using a Rectified Linear Unit (ReLU).

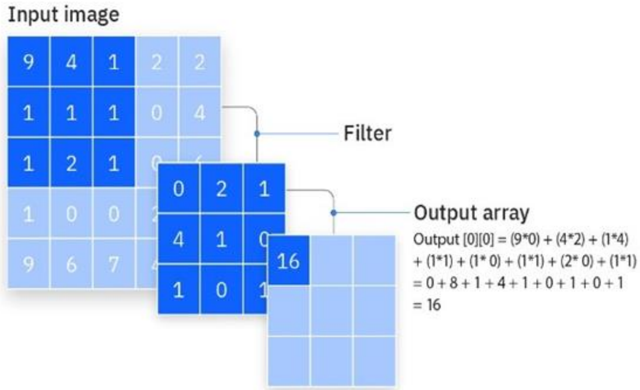


Fig 4: Convolutional Matrix Representation

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Leaky ReLU

The normal ReLU function, which causes the neural network to die during training, was used to overcome the dying ReLU problem with the creation of this activation function.

Mathematical representation of the Leaky ReLU function is:

LeakyReLU(x)=max(alpha*x,x)

In the above equation,we see parameter x,The leaky ReLU will return the max value between alpha*x , x. "alpha" is small positive constant.

Leaky ReLU function converts negative values to make them close to 0 but not 0 which helps in overcoming the dying ReLU issue which arises from standard ReLU function.

Let's now examine an example shown in figure 5 to observe how the function maps the neural network layer's outputs to a visual representation.

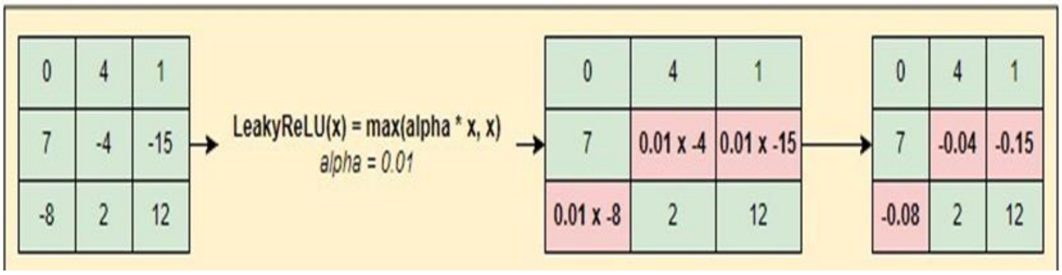


Fig.5: Mathematical representation of Leaky ReLU

The function is shown in the figure 6 as receiving a list of values, which may or may not be positive or negative. The constant alpha will multiply all negative numbers so that they are close zero.

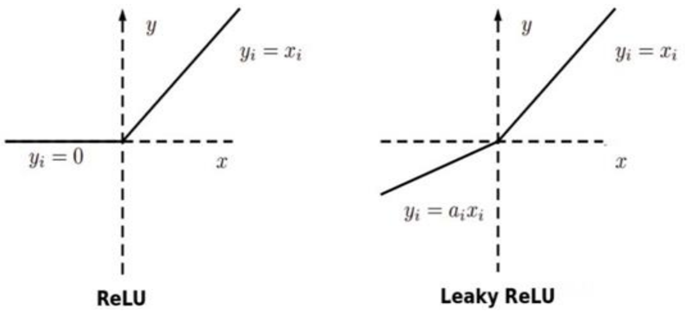


Fig 6: Graphical representation of Leaky ReLU

Batch Normalization

Batch Normalization is used in between a neural network's layers as opposed to in the raw data. Instead of using complete dataset, it divides the dataset into mini-batches. It facilitates quicker training and greater learning rates, which makes learning simpler. We may observe a typical feed-forward neural network in the following picture: The network's output is represented by y, the inputs by x_i, the neuronal output by z, and the activation function output by a.

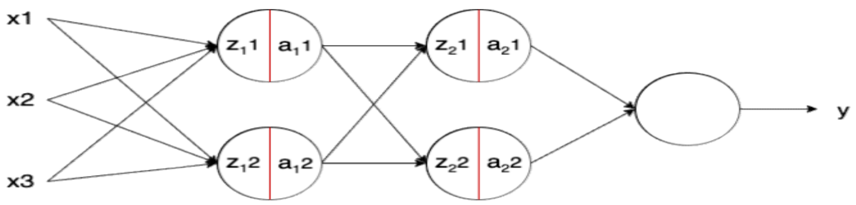


Fig 7: Working of Batch Normalization

4. Results and Discussion

SEGAN segmentation of liver tumors produced encouraging segmentation findings. When used to distinguish tumor borders from surrounding healthy liver tissues in medical imaging, the system exhibits great accuracy and resilience. SEGAN routinely outperforms other segmentation approaches in terms of performance measures after difficult testing and validation. Moreover, visual examination of segmented pictures for qualitative assessment shows that SEGAN can precisely define tumor borders even in difficult circumstances when the tumor has uneven forms, a variety of textures, and little contrast with the surrounding tissues.

As shown in Figure 8, the partial segmentation result is chosen from the test set. The original picture is shown in column one, and the segmentation results using the suggested model (SegAN) are shown in column two.

Input image Segmented image

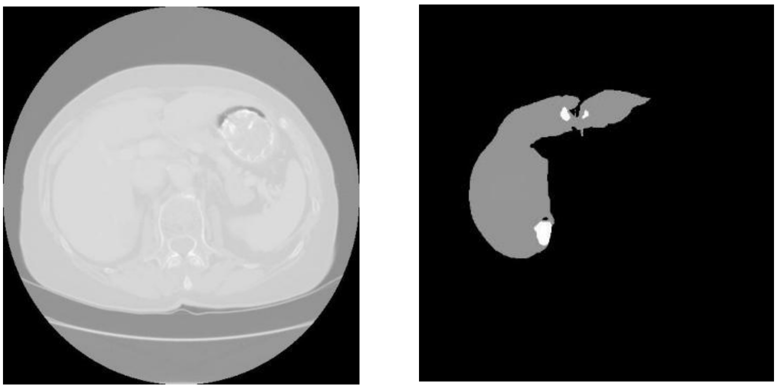


Fig 8: Representation of segmentation results

Applying the proposed approach resulted in clear segmentation results for the liver tumor, demonstrating separation and characterization. The program efficiently identifies and highlights the characteristics of the liver tumor including size, shape, and volume through accurate computational procedures, improving the precision of the diagnosis and supporting the treatment planning process. With a dependable tool for more thorough and accurate study of liver tumors, this development represents a major improvement in medical imaging technology and will ultimately lead to better patient treatment and outcomes.

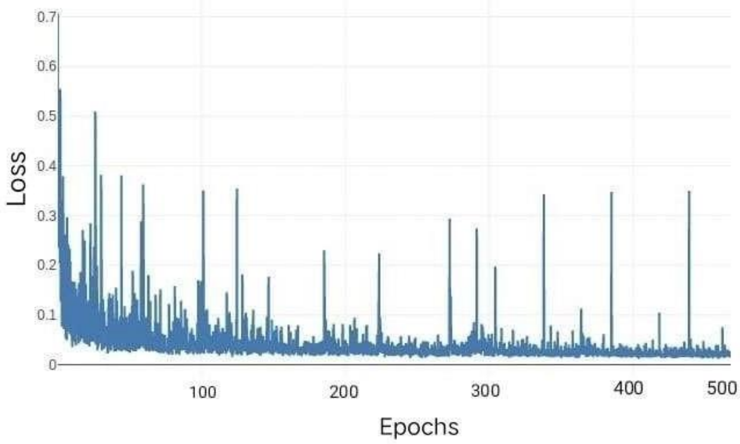


Fig 9: Loss Curve

As shown in the Figure 9, the graph represents the dice loss function, as epochs increase on the x-axis, the y-axis represents the degree of loss function. Initially, the loss is high, but it keeps decreasing over epochs, showing a downward trend indicating that the model is improving its performance over time.

However, because the network contains a lot of parameters, training takes a long time when there aren't enough computational resources. During training, the encoder-decoder structure is utilized to extract features and recover 3D pictures as the data consists of a 3D volume of the liver. Consequently, it uses plenty of memory when training the model, which is a complicated model. The images need too much memory; therefore, we may shorten the training time of the model by optimizing the network architecture and modifying memory efficiency. Furthermore, a variety of techniques within the realm of medical imaging processing makes extensive use of CNNs and GANs. So, it is beneficial to do in-depth study on the development and implementation of SegAN within the realm of medical imaging processing.

5. Conclusion

In order to improve segmentation accuracy, this research presents a unique technique for semantic segmentation called the Semantic Enhancement Generative Adversarial Network (SegAN), which makes use of a Dice loss function. The well-known LiTS Challenge dataset, a standard for liver tumor segmentation in medical pictures, is used for experimental assessments in this work. Interestingly, SegAN outperforms its main use case, broadening its scope to include many medical picture tasks outside of liver tumor segmentation. The usefulness of the system for generic semantic segmentation tasks across several domains highlights its versatility even further. By offering a flexible model that can handle both particular medical imaging problems and more general semantic segmentation applications, this research advances the field and illustrates how computer vision solutions for a variety of image analysis tasks might benefit from it.

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