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Medical Image Analysis for Liver Tumor Localization and Segmentation using Deep Learning

Doddi Dhanush[1], Amiti Nikhita[2], Gampala Sivamani[3], Gedala Durga Sai Saketh[4], Manyam Nitish[5], R. Cristin[6]

[1,2,3,4,5,6] Department of Computer Science & Engineering, GMR Institute of Technology, Rajam, Vizianagaram

[1]20341A0551@gmrit.edu.in, [2]20341A0511@gmrit.edu.in, [3]20341A0558@gmrit.edu.in, [4]20341A0562@gmrit.edu.in, [5]19345A05A5@gmrit.edu.in, [6]cristin.r@gmrit.edu.in

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ABSTRACT—

Liver cancer is a life threatening illness and one of the fastest growing cancer in the world. Segmenting liver tumors from computed tomography(CT) images is crucial for the diagnosis and management of liver cancer. The variety of appearances, hazy borders, variable densities, forms and sizes of lesions of tumors makes it challenging .This work introduces a liver tumor segmentation method based on the Liver Tumor Segmentation (LITS) dataset. U-net model is used to segment the lesions in the tumor. A convolutional neural network architecture created especially for semantic segmentation problems is used to implement a U-net model for liver tumor segmentation. U-Net and Seg-Net models demonstrate better segmentation performance by utilizing the extensive annotated data present in the LITS dataset. To produce the segmentation output , the encoder down samples the input picture through convolutional and pooling layers, while the decoder up samples the feature map. The last layer is sigmoid activation function the task is likely binary segmentation. The outcomes of the experiment confirm the efficacy of the suggested method, demonstrating its potential to improve diagnostic precision in medical environments. Dice- coefficient, Dice-loss,F1 score are the metrics used to calculate the performance of the segmented images

Keywords: Segmentation, CT images, U-Net, Seg-Net, Binary segmentation.

I. INTRODUCTION

Medical imaging and diagnostic procedures that are crucial to the early detection and focused treatment of liver diseases include the localization and segmentation of liver tumors. The liver is a vital organ that carries out several processes, including metabolism, detoxification, and protein synthesis. However, a variety of clinical conditions might impact it, such as tumors, which can be either benign or malignant.

Accurate localization and segmentation of liver cancers is essential for clinical decision making and therapy planning. Advances in medical imaging technology, particularly computed tomography (CT) and magnetic resonance imaging (MRI), have radically changed the way liver disorders are diagnosed and tracked. Physicians can detect and evaluate liver tumors thanks to these imaging modalities, which provide accurate cross-sectional pictures..

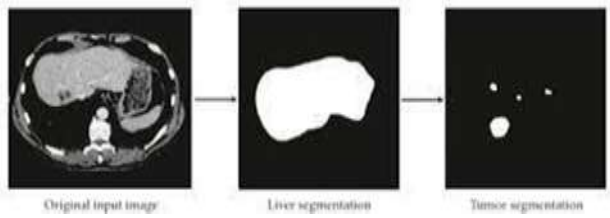

Fig1. Sample segmentated image.

The first stage in localizing liver cancers is determining whether the tumors are there, where they are, and how big they are inside the liver. Choosing the optimal course of action for therapy and gaining a baseline understanding of the illness depend on this initial phase. Once a tumor has been located, segmentation is utilized to determine the borders between it and the surrounding healthy tissue.

Clearly defining the objectives and selecting the imaging modalities (such as CT or MRI) is the first step in this study on the localization and segmentation of liver cancers. Next, a diverse and annotated dataset is collected to ensure representation of a range of tumor sizes, shapes, and locations for the purpose of training and evaluating the model. When constructing algorithms utilizing region- based or pixel-based approaches, explicit feature extraction is not required. The dataset is split up into training, validation, and testing sets in order to train and assess the model. To assess the performance of the model, metrics are employed.

II. RELATED WORKS

MICCAI Liver Tumor Segmentation (LiTS) Challenge Dataset is a widely used dataset for liver tumor segmentation containing CT scans with annotated tumors. Another benchmark dataset for liver tumor segmentation in CT scans is Liver Tumor Segmentation Benchmark (LITS). 3Dircadb is also a dataset containing 3D reconstructed images of the liver with tumors . Public benchmarks like SLiver have facilitated comparative analysis among various segmentation and classification methods. The manually annotated or expert-verified segmentation or classification labels used as reference data for training and evaluating algorithms are ground Truth.

A feature vector is a numerical representation of an item or region made up of different quantitative descriptors including texture features, intensity statistics, shape attributes, etc. that is usually retrieved from medical pictures. A classifier is a machine learning algorithm that has been taught to identify patterns in training data and apply class labels (such as tumor vs. non-tumor) to input feature vectors. In a binary classification problem, the method uses input information to determine which of two classes—tumor vs. non-tumor, for example—it belongs to. In the Multi-Class Classification job, distinct types of liver tumors or other anatomical structures can be distinguished by assigning one of several class labels to input feature vectors by the algorithm.

Ensemble learning is a machine learning technique that reduces overfitting and increases robustness in the classification of liver tumors by training and combining numerous classifiers. A confusion matrix is a table that displays the numbers of true positive, true negative, false positive, and false negative predictions and is used to assess how well a classification system performs. Conventional techniques, which are frequently followed by machine learning classifiers, use characteristics like texture, shape, and intensity to define tumors. examining the tumor's shape to distinguish between various liver tumor kinds or stages. Texture analysis is the process of removing textual elements from pictures in order to represent the variety of tumors. Because U-Net captures spatial information well, it is a preferred design for medical picture segmentation.

DeepLab uses atrous convolution to capture multi-scale context, which is why it is well-known for its exceptional performance in semantic segmentation tasks. CNNs in three dimensions volumetric data, such as medical scans, can benefit from the use of three-dimensional convolutions to collect spatial information across several slices. Another deep learning architecture for semantic segmentation problems, such as liver tumor segmentation, is the Fully Convolutional Network (FCN). Entire images can be processed effectively by FCNs in a single forward pass. One popular machine learning technique for categorization tasks is called Random Forest. Random forests can be trained using manually created characteristics taken from medical pictures in the context of liver tumor segmentation and classification. A supervised learning technique used for both regression and classification problems is called Support Vector Machine (SVM). SVM can be trained on features taken from medical pictures for the purpose of classifying liver cancers into several groups. K-Means For clustering tasks, clustering is a straightforward unsupervised learning approach. K-means clustering can be used in liver tumor segmentation to divide medical image voxels or pixels into tumor and non-tumor regions according to texture or intensity characteristics. A technique called "region growing" is used to segment images by repeatedly growing regions from seed points that have similar characteristics (like intensity, for example). Tumor segmentation in medical pictures is one of its common uses. A morphological technique called the Watershed Transform is used to segment images, especially those containing objects whose boundaries are not clearly defined. The watershed transform can be used to help define tumor boundaries based on intensity gradients in liver tumor segmentation. Active Contour Models, often known as Snakes, are deformable models that, depending on features in the image, deform repeatedly towards object boundaries. Liver tumors in medical pictures can be accurately delineated with the use of active contour models. Depending on the particular needs and properties of the data, these techniques can be applied singly or in combination.. In order to obtain reliable and precise segmentation and classification of liver tumors, researchers frequently investigate various algorithmic techniques. Every approach has advantages and disadvantages, and the selection process is frequently influenced by elements like the type of data being used, the available processing power, and the particular needs of the application. To get the best results for segmenting and classifying liver tumors, researchers frequently test out various approaches and combinations. The process of identifying and classifying tumors within liver imaging data, such as CT or MRI scans, is known as hepatic tumor segmentation and classification. The process of locating and defining tumor sections within the images is known as segmentation. Deep learning-based approaches like U-Net or region-growing techniques are frequently used in this procedure. On the other hand, classification entails labeling segmented sections in order to distinguish between tissues that are tumorous and those that are not, as well as to classify tumors into various categories or stages. Machine learning techniques like support vector machines, random forests, or deep learning classifiers based on variables collected from the segmented regions—such intensity, texture, or shape characteristics—are frequently used to do this.

Metrics like the Dice similarity coefficient, accuracy, precision, recall, or area under the ROC curve are commonly used to evaluate segmentation and classification performance because they offer quantifiable assessments of algorithm efficacy.The ground truth and anticipated segmentations' overlap is measured using the Dice Similarity Coefficient (DSC). The model's sensitivity and specificity indicate how well it can distinguish between positive and negative cases. The three conventional measures for assessing classification performance are accuracy, precision, and recall.

III. METHODOLOGY

3.1 Datasets LITS:

There are 194 CT scans with lesions out of 201 computed tomography pictures of the abdomen in the LiTS benchmark dataset. Several clinical locations worldwide offer the data and segmentations.

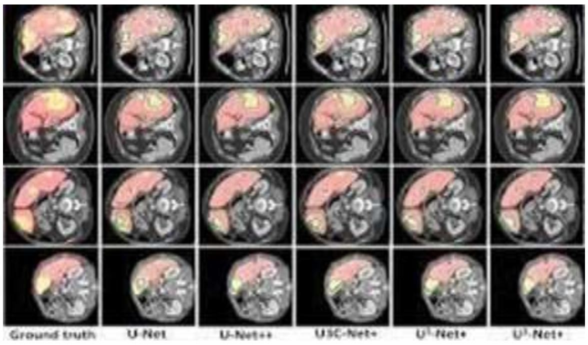

Fig2. Lits Dataset

3DIRCADb:

In 75% of cases, the 3D CT-scans of 10 women and 10 men with hepatic tumors make up the 3D-IRCADb-01 database. The 20 folders, each representing 20 distinct patients, can be downloaded separately or together.

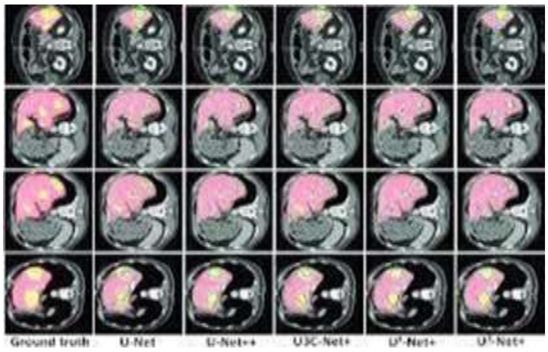

Fig3. 3DIRCADb dataset

3.2 Preprocessing

Preprocessing, which creates processed pictures from raw CT scans that can distinguish the liver's characteristics from those of other human organs, is an essential step in the image segmentation process. Using a zero mean and unit variance for every image, we improved the contrast and normalized the pictures.

3.3 U-Net

Convolutional neural network design UNet was created specifically for biomedical picture segmentation tasks, par- ticularly in situations when the amount of labeled data that is accessible is constrained. In 2015, Olaf Ronneberger, Philipp Fisch-er, and Thomas Brox presented it. Because of its U-shaped architecture, the place is called "UNet".

This is the general operation of UNet:

Encoder-Decoder Configuration: The encoder-decoder architecture is used by UNet. The encoder-decoder struc- ture of UNet, on the other hand, is more symmetrical and forms a U. While the decoder retrieves spatial information and creates segmentation masks, the encoder gathers con- text and extracts high-level features from the input image.

Contracting Path (Encoder): Convolutional and pooling layers are grouped in a contracting path to form the encod- er. These layers increase the number of feature channels while gradually decreasing the input image's spatial dimen- sions. By using this method, abstract features can be ex- tracted from the input image and context can be captured.

Expanding Path (Decoder): The decoder is the counter- part of the encoder and is in charge of producing high- resolution segmentation masks by upsampling the low- resolution feature maps. To restore spatial features lost dur- ing the encoding stage, UNet uses concatenation with fea- ture maps from the contracted path and upsampling layers, such as transposed convolutions or bilinear interpolation.

Skip Connections: The utilization of skip connections, which concatenate feature maps from the contracting path with comparable feature maps in the expanding path, is one of the primary characteristics of UNet. By allowing the decoder to access both local and global data, these skip links enhance segmentation accuracy and help preserve fine-grained details.

Final Layer: A convolutional layer with a softmax activa- tion function is frequently employed at the conclusion of the decoder to generate a probability distribution over the various classes for every pixel. This distribution shows the probability that every pixel falls into a specific semantic category.

Training: A sizable dataset of annotated photos, with each pixel tagged with the corresponding class, is commonly used to train UNet. Using methods like backpropagation and stochastic gradient descent, the model learns to mini-mize the difference between the predicted segmentation masks and the ground truth labels during training.

In domains where limited labeled data is available, includ- ing satellite image segmentation, UNet has gained populari- ty in addition to the biomedical image segmentation field. It is efficient at capturing minute details and producing pre- cise segmentation results thanks to its symmetric architec- ture and skip connections.

A computer vision task called image segmentation divides an image into several sections by giving each pixel in the picture a label. Compared to object classification, which labels the object, or object detection, which creates a bounding box around the identified object, it offers a great deal more information about an image. Applications for segmentation in the real world include clothing segmentation, flood maps, medical imaging, self-driving automobiles, etc. Segmentation is helpful. Two categories of picture segmentation exist: Segment data semantically by assigning a label to each pixel.

Segmenting an instance of an object involves classifying each pixel and distinguishing each instance. The semantic segmentation method known as U-Net was first suggested for use in medical imaging segmentation. It is among the first segmentation models for deep learning, and many GAN variations, such the Pix2Pix generator, also use the U-Net architecture.

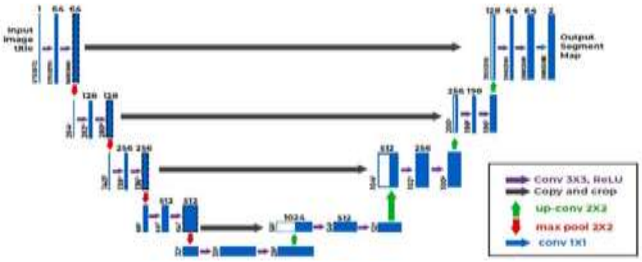

Fig4.U-Net architecture

3.4 Seg-Net

A deep learning architecture called SegNet was created for computer vision problems involving semantic segmentation. By giving a class name to every pixel in an image, semantic segmentation divides the image into segments that represent several item types or areas of interest.

This is an explanation of SegNet's operation:

Encoder-Decoder Architecture: SegNet employs an encoder-decoder design, which is divided into two primary components: the encoder network and the decoder network.

Encoder : Typically, the encoder consists of a convolutional neural network (CNN) that goes through a number of convolutional and pooling layers to process the input image and extract high-level information. These layers increase the number of feature channels while gradually decreasing the input's spatial dimensions.

Decoder: The low-resolution feature maps that the encoder creates must be upsampled by the decoder network in order to provide high-resolution segmentation masks. Upsampling layers are used, frequently in conjunction with convolutional layers, to progressively restore the spatial information that were lost during the encoding process.

Skip connections : The utilization of skip connections between corresponding encoder and decoder layers is one of SegNet's primary characteristics. By keeping fine- grained details, skip connections allow the decoder to access detailed spatial information from previous encoder stages, which enhances segmentation mask accuracy.

Softmax layer: A softmax layer is usually employed at the conclusion of the decoder to provide a probability distribution over the various classes for every pixel. This distribution shows the probability that every pixel falls into a specific semantic category.

Training : A sizable dataset of annotated photos, where each pixel is tagged with the appropriate class, is used to train SegNet. Using strategies like gradient descent and backpropagation, the model learns to minimize the difference between the ground truth labels and the anticipated segmentation masks during training.

All things considered, SegNet is an effective design that strikes a decent compromise between computational economy and accuracy for semantic segmentation tasks. It has been extensively employed in many different fields, such as robotics scene comprehension, medical picture analysis, and autonomous driving.

Semantic segmentation is modeled by SegNet. The fundamental design for trainable segmentation comprises an encoder network, a corresponding decoder network, and a pixel-wise classification layer. The encoder network's design is topologically identical to the VGG16 network's 13 convolutional layers. The low resolution encoder feature maps must be mapped to full input resolution feature maps by the decoder network in order to perform pixel-by-pixel classification. The way the decoder upsamples its lower resolution input feature maps is where SegNet's innovation resides. To be more precise, the decoder performs non- linear upsampling using pooling indices that are calculated during the max-pooling stage of the matching encoder.

Applications involving scene interpretation served as SegNet's main driving force. As a result, during inference, it is made to be as efficient as possible with regard to memory and processing time. Compared to other rival architectures, it has a notably smaller amount of trainable parameters. Additionally, we conducted a controlled benchmark using SegNet and other topologies for the segmentation tasks of SUN RGB-D indoor scenes and road scenes. Compared to previous designs, we demonstrate that SegNet offers competitive inference time and better memory efficiency.

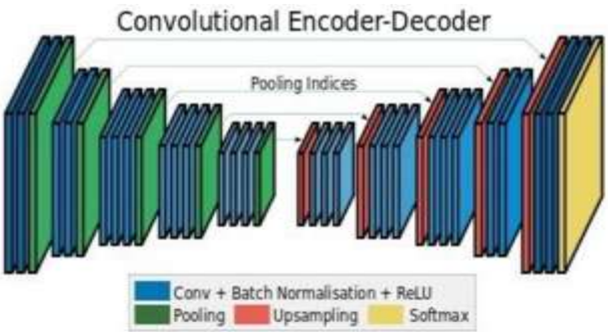

Fig5. SegNet architecture

3.5 Work flow

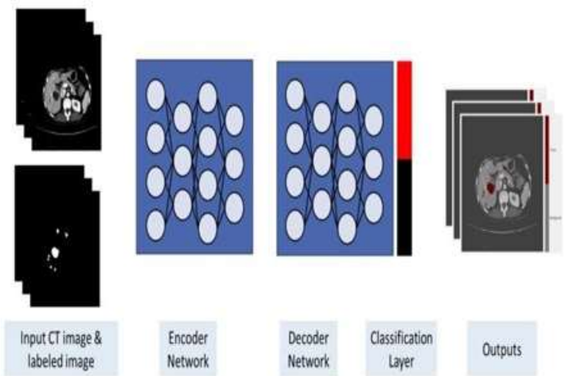

Fig6. Workflow

IV. RESULTS AND DISCUSSION

To sum up, the segmentation model based on encoder decoders exhibits encouraging outcomes when it comes to producing images of segmented livers. More testing and fine-tuning can offer better results. The quality of the segmented images produced is indicated by the accuracy, sensitivity, and dice coefficient. It is crucial to take into account both qualitative and quantitative factors when assessing how well these models work.

V. EXPERIMENT RESULTS

The model results are evaluated using Accuracy, Sensitivity, Dice coefficient and they are shown in Table 1.

Metrics	Accuracy	Sensitivity	Dice coefficient
U-Net	96%	94%	0.76
Seg-Net	98%	97%	0.89

VI. CONCLUSION

This paper describes the procedures and code for a liver segmentation model based on the encoder and decoder architecture. The model's capability is evaluated using the dice coefficient scores, which indicate the quality of the segmented images, accuracy, and sensitivity. The offered code can be used as a jumping off point for additional study and testing related to liver segmentation tasks. See the provided code comments as well as the comments in the section on individual codes for further details and explanations of the codes.

VII. REFERENCES

[1]. Jiang, H., Shi, T., Bai, Z., & Huang, L. (2019). Ahcnet:An application of attention mechanism and hybrid connection for liver tumor segmentation in ct volumes. Ieee Access, 7, 24898-24909.

[2]. Tran, S. T., Cheng, C. H., & Liu, D. G. (2020). A

multiple layer U-Net, U n-Net, for liver and liver tumor segmentation in CT. IEEE Access, 9, 3752-3764

[3]. Lyu, F., Ma, A. J., Yip, T. C. F., Wong, G. L. H., &

Yuen, P. C. (2021). Weakly supervised liver tumor segmentation using couinaud segment annotation. IEEE Transactions on Medical Imaging, 41(5), 1138-1149.

[4]. Chen, L., Song, H., Wang, C., Cui, Y., Yang, J., Hu, X., & Zhang, L. (2019). Liver tumor segmentation in CT volumes using an adversarial densely connected network. BMC bioinformatics, 20, 1-13.

[5]. Zhang, J., Xie, Y., Zhang, P., Chen, H., Xia, Y., & Shen, C. (2019, August). Light-Weight Hybrid Convolutional Network for Liver Tumor Segmentation. In IJCAI (Vol. 19, pp. 4271-4277).

[6]. Bilic, P., Christ, P., Li, H. B., Vorontsov, E., Ben- Cohen, A., Kaissis, G., ... & Menze, B. (2023). The liver tumor segmentation benchmark (lits). Medical Image Analysis, 84, 102680.

[7]. Li, W., Jia, F., & Hu, Q. (2015). Automatic segmentation of liver tumor in CT images with deep convolutional neural networks. Journal of Computer and Communications, 3(11), 146-151..

[8]Heker, M., & Greenspan, H. Joint liver lesion segmentation and classification via transfer learning. arXiv 2020. arXiv preprint arXiv:2004.12352.

[9]. Dong, X., Zhou, Y., Wang, L., Peng, J., Lou, Y., & Fan, Y. (2020). Liver cancer detection using hybridized fully convolutional neural network based on deep learning framework. IEEE Access, 8, 129889-129898.

[10] Moritz Gross, Michael Spektor, Ariel Jaffe, Ahmet S. Kucukkaya, Simon Iseke, Stefan P.Haider. Improved performance and consistency of deep learning 3D liver segmentation with heterogeneous cancer stages in magnetic resonance imaging.

[11] Rendong Wang, Yida He, Cuiping Yao, Sijia Wang, Yuan Xue, Zhenxi Zhang, Jing Wang, Xiaolong Liu.Classification and Segmentation of Hyperspectral Data of Hepatocellular Carcinoma Samples Using 1-D Convolutional Neural Network

[12] GrzegorzChlebus, Andrea Schenk, Jan Hendrik Moltz, Horst Karl Hahn & Hans Meine .Automatic liver tumor segmentation in CT with fully convolutional neural networks and object-based postprocessing.

[13] Annika Gerken, Grzegorz Chlebus, Hans Meine, Felix Thielke, Farina Kock,Tobias Paulus, Nasreddin Abolmaali, Andrea Schenk. Liver Tumor Segmentation in Late-phase MRI using Multi-model Training and an Anisotropic U- Net.

[14] Saumiya S,S. Wilfred Franklin.Unifed automated deep learning framework for segmentation and classifcation of liver tumors.

[15] Dr. S. P. Tamizhselvi, Dr. P. Revathy,Dr. I. Ambika,Dr. E. Manogar, Mrs. G. Renganayagi, Dr. C. Mahiba .Analysis of Cancerous Liver MRI Image using Various Segmentation Methods