Image-Guided Pre-surgical Assessments Using Deep Learning-Based Methods for Liver Segmentation from CT and MRI Images

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Abstract

Medical imaging powered by artificial intelligence (AI) can help doctors make proper treatment decisions, plan surgeries for organ transplants, and help oncologists improve treatment plans for cancer patients who are diagnosed early. CT or MR images could be used to detect cancer in its early stages, which would prevent millions of deaths worldwide. The purpose of this research is to present a deep learning-based algorithm that can assist radiologists in planning liver transplantations and cancer detection by segmenting liver images from abdominal CT and MR images. The proposed model was trained on a standard dataset of CHAOS challenge for CT, and MRI images. Our model has accurately performed segmentation of the liver from the abdominal images with a dice coefficient of 0.983 on CT images and a dice coefficient of 0.935 on MRI T1 Out-phase modality.

Keywords- *Liver cancer, segmentation, CT, MRI, deep-learning, artificial intelligence*

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1. Introduction

The liver is the largest internal organ residing just under the right lung of the human body below the right ribs. There are about 100 different kinds of liver disease. They all have one thing in common: they all entail liver impairment that affects its capacity to operate normally. Several liver diseases damage the liver, causing liver failures such as Cirrhosis, Hepatitis, Alcoholic liver disease, etc. And the most common and minacious one is liver cancer. Liver cancer starts to sow its seeds when cells in the body begin to grow out of control [1]. A cancerous growth in the liver destroys liver cells and impairs its capacity to function normally [2]. Compared to other cancers liver cancer has been observed to have a low survival rate. When a person's liver fails due to disease or injury, they require a liver transplant. However, early diagnosis and vital treatment can drastically improve the chances of survival for people with liver cancer and other liver diseases [3]. The roadmap for the diagnosis of liver diseases like cancer could be followed either by the help of an expert who has looked at cell or tissue samples under a microscope or by conducting the tests on the cells' proteins, DNA, and RNA that comprehend doctors about cancer residence [5].

The results of these diagnostic tests are very important when choosing the best treatment options. Currently, several imaging modalities are available such as ultrasonography (US), computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) for the detection and characterization of focal liver tumors. Out of these, abdominal CT or MRI scans were found to produce detailed images of the liver and other organs in the abdomen. Along with the early diagnosis, to improve the chances of survival of a patient with liver cancer early detection of the tumor is also necessary. As accurate detection of malignant liver disease remains crucial to the patient and also as benign liver tumors are very common, liver-imaging strategies should include liver lesion characterization as an equally important task [6]. This has fueled the development of AI systems for cancer detection using medical images. A sophisticated method for extracting a large number of characteristics from pictures using a combination of radiological imaging and AI may be used to provide minute data about tissue, organ anatomy, blood arteries, and abnormalities in the organs. It may also be used to classify lesions such as liver tumors and predict prognosis using computed tomography (CT) and magnetic resonance imaging (MRI) image data. [7]. CT imaging is the most commonly used method for diagnosis of liver tumors because of its rapid inspection, high quality, and low cost [8]. Manual segmentation techniques are time-consuming and prone to errors. As a result, deep learning applications have increased the relevance of automated segmentation methods. When it comes to liver segmentation methodologies, artificial intelligence-based systems perform exceptionally well. Automated segmentation approaches have shown significant promise in enabling clinical practices to provide more precise medical treatment which uses deep learning [8].

In this study, image segmentation was used to detect liver tumors for their diagnostic significance. Artificial intelligence (AI) is used in this study to segment CT and MR liver images. A dataset was preprocessed according to the need of the liver segmentation tasks and then implemented on a deep-learning-based Res-Unet segmentation model and the dataset was trained to elucidate the liver accurately, outperforming various existing models.

2. Literature Review

To successfully implement a segmentation model we have referred to various research papers and articles. The first paper was CHAOS Challenge - combined (CT-MR) healthy abdominal organ segmentation by AE Kavur [9]. It was a challenge in which participating groups presented different approaches for five different but complementary tasks designed for single/multi organs and cross-modality segmentations and were analyzed based on multiple perspectives. According to the observations, organ-specific models performed quite better as compared to multi-tasking DL models designed to segment all organs. Some of the successful models performed better with their multi-organ versions as well. Research for developing effective algorithms that can support real- world medical applications could benefit from further analysis of the success and failure of single versus multi- organ and cross-modal segmentations. We referred to this paper to better understand the dataset we worked upon and to pick the suitable network architecture for our work as the participants proposed various segmentation models.

The second paper was Deep Learning-based Liver Cancer Segmentation from Computed Tomography Images by Dr. Kinde Anlay in which, they developed a deep learning-based segmentation algorithm for analyzing CT scan images of the abdomen in order to identify liver and tumor regions [10]. They worked upon 3D-IRCADb-01 (3D Image Reconstruction for Comparison of Algorithm Database) and LITS (Liver Tumor Segmentation) Challenge datasets and built three separate UNet models one for liver segmentation and the other two for segmentation of tumors from the segmented liver and the abdominal CT scan image. A number of performance metrics were used to evaluate the performance of the segmentation method, including dice scores, Jaccard similarity coefficients (JSC), accuracy, and symmetric volume difference (SVD). Segmentation of liver was achieved with a dice score of 0.96.

Sultan Almotairi's proposed Modified SegNet for Liver Tumor Segmentation in CT Scans. SegNet Architecture is a deep learning-based approach in this paper. It was composed primarily of a hierarchy of encoder-decoder layers using the trained VGG-16 image classification network [11]. Originally, the architecture was designed for semantic pixel-by-pixel classification of road scenes; the architecture was adopted and modified by the authors of this paper to fit hepatic CT segmentation and classification. They used the same dataset as in the previous paper mentioned above, the 3D-IRCADb-01 dataset composed of 3D CT scans. Before combining the data, they trained and enhanced the data by reading batches of training data, augmenting the data, and passing the augmented data to the training algorithm. On a pixel-by-pixel basis, the output results of this SegNet architecture categorization were compared to their respective ground truth. During their training phase, they were able to attain tumor accuracy of up to 99.9%. They cited SegNet Architecture as having a significant advantage over typical auto- encoder architecture in terms of training time, memory needs, and accuracy.

The fourth one was Modified U-Net for liver cancer segmentation from CT images with a new class balancing method by Yodit Abebe Ayalew [12]. In order to reduce network complexity and improve segmentation performance, the researchers proposed a modification to the original UNet architecture. To modify the original model, fewer filters were added to each convolutional block in the contracting path and an additional batch normalization and dropout layer was added after each convolutional block. The UNet model was modified and introduced a new class balancing method to minimize the class imbalance problem. Three separate models with similar architectures were used for training. The first model trained for abdominal CT scan images with liver annotations for liver segmentation produced the DSCs of 0.9511 and 0.9633 obtained after the 100th epoch for training and validation data. The final losses for training and validation were − 1.7567 and − 2.1753 respectively.

Yuki Enokiya on Automatic Liver Segmentation Using U-Net with Wasserstein GANs [13]. They used Wasserstein GAN to improve U-Net's training. The 3D-IRCADb-01 dataset was used to develop an adversarial learning network for segmenting medical images. A network trained on small datasets improved liver segmentation accuracy (Dice value) from 88% to 92% and from 92% to 93% with 33 and 392 training data sets, respectively. Using this proposed adversarial training, dice values improved by about 3%–5%.

K Wang, A Mamidipalli, and T. Retson presented their work on automated CT and MRI Liver Segmentation and Biometry Using a Generalized Convolutional Neural Network [14]. Data was curated from multiple sources and was a distinct multi-institutional dataset (498 subjects). Using 330 abdominal MRI and CT examinations, a two- dimensional U-Net CNN was trained in two stages for liver segmentation. A validation experiment was conducted to assess the accuracy of the initial and final multimodal CNN for liver segmentation using 50 multi-echo 2D and 3D SPGR MRI examinations, the initial CNN was evaluated for its accuracy in liver segmentation in the first experiment. Using all four types of images from the internal validation dataset and the external validation dataset, we compared the accuracy of the initial CNN and multimodal CNN for liver segmentation. Segmentation accuracy was evaluated by computing Dice scores. Final Dice scores were 0.94 ± 0.06 for CT (n = 230), 0.95 ± 0.03 (n = 100) for T1-weighted MRI, and 0.92 ± 0.05 for T2*-weighted MRI (n = 168). The results of this study have demonstrated the feasibility of a CNN in performing liver segmentation across different imaging techniques and modalities. The analysis of various segmentation networks for the liver tumors is shown in table 1.

Table 1. Analysis of various segmentation networks on CT images.

Sr. No.	Name of Authors	Details of Publication	Methodology
1	X. Dong, Y. Zhou, L. Wang, J. Peng, Y. Lou and Y. Fan,	"Liver Cancer Detection Using Hybridized Fully Convolutional Neural Network Based on Deep Learning Framework," in IEEE Access, vol. 8, pp. 129889-129898, 2020, DOI: 10.1109/ACCESS.2020.3006362.	Hybridized Fully Convolutional Neural Network (HFCNN) has been proposed for liver tumor segmentation, which has been modeled mathematically to resolve the current issue of liver cancer.

2	Weiwei Wu, Shuicai Wu, Zhuhuang Zhou, Rui Zhang, Yanhua Zhang	"3D Liver Tumor Segmentation in CT Images Using Improved Fuzzy C- Means and Graph Cuts", BioMed Research International, vol. 2017, Article ID 5207685, 11 pages, 2017. h ttps://doi.org/10.1155/2017/52 07685	In place of the Euclidean metric, a novel distance function was employed in the segmentation stage of the alternative fuzzy clustering algorithm. For the purpose of labeling pixels for the final Random Walker segmentation, FCM with cuckoo optimization was used.
3	Almotairi S, Kareem G, Aouf M, Almutairi B, Salem MA.	Liver Tumor Segmentation in CT Scans Using Modified SegNet. Sensors (Basel). 2020;20(5):1516. Published 2020 Mar 10. doi:10.3390/s20051516	The semantic pixel-by-pixel classification of street scenes has been adopted and modified to match the Liver CT segmentation and classification. The architecture used here is called SegNet.
4	Ayalew, Y.A., Fante, K.A. & Mohammed, M.	Modified U-Net for liver cancer segmentation from computed tomography images with a new class balancing method. BMC Biomed eng 3, 4 (2021). https://doi.org/10.1186/s42490 -021-00050-y	Three separate UNet models were used. One is for liver segmentation and the other two is for tumor segmentation from segmented liver and abdominal CT scan images.

3. Methodology

3.1 Dataset

The dataset used in this work is taken from the CHAOS (Combined Healthy Abdominal Organ Segmentation) Challenge, which aims to segment abdominal organs from CT and MRI data [9]. The dataset used across this application contains CT and MR images in DICOM format. As in CT datasets, only livers were elucidated and in MRI datasets, livers, left/right kidneys, and spleens were elucidated. The CT dataset we worked upon for liver segmentation consisted of 20 training and 20 testing cases. Train data contains both DICOM images and their respective ground truth masks around 2,875 images each. The MRI dataset contains 20 training cases with ground truths and 20 testing cases with T1-Dual and T2 SPIR sequences.

3.2 Experimentation

The implementation of the model was done using Google Colab (Collaboratory) which uses Python 3.9.6 version. CT and MR images were in DICOM format which needed to be converted into PNG image format. As PNG preserves the image quality, we opted for it over JPEG as it is a lossless format. Preprocessing of images was required, to perform the segmentation as the obtained images were larger, and processing the whole images with these sizes is difficult due to limited GPU memory. Resizing was done on the images using python algorithms involving CV interpolation and LSDWT methods, the size were reduced to half of the original size i.e. to 256 X 256 from 512512. Both the methods were interpreted based on comparing parameters such as MSE and PSNR calculations. This came out to be better for the CV interpolation method.

3.3 Segmentation Technique

3.3.1The segmentation algorithm

The algorithm is based on U-Net architecture, which is a network based on the fully convolutional network principle [15]. It consists of an encoder that extracts features and a decoder that reconstructs images. Skip connection is also used to integrate low-and high-level information, allowing for precise localization. Medical image analysis frequently employs such a network design. Repeating a succession of 2D slice segmentation is used to segment a 3D structure, such as the liver. The consistency across slices is lost since this technique does not contain context information along the z-axis.

3.3.2Network Architecture (Res-Unet)

On the basis of Res-Unet Architecture, a segmentation model was created. Deep Residual Unet is referred to as Res-Unet. For semantic segmentation, an encoder-decoder architecture was created. A fully convolutional neural network called Res-Unet was created with the goal of achieving excellent performance with minimum parameters. In comparison to the current Unet architecture, it is an improvement. The performance of the multi- layer neural networks can be improved by going deeper; however, it could interfere with the training and cause degeneration. The residual neural network was introduced by K. He, X. Zhang, S. Ren, and J. Sun to simplify training and alleviate the deterioration issue [16]. An encoding network, a decoding network, and a bridge connecting the two networks make up the Res-Unet. We took the basic deep Res-Unet model proposed by Zhengxin Zhang and Qingjie Liu [17]. This work utilizes 9-level architecture of deep ResUnet for Liver segmentation, as shown in Fig. 1.

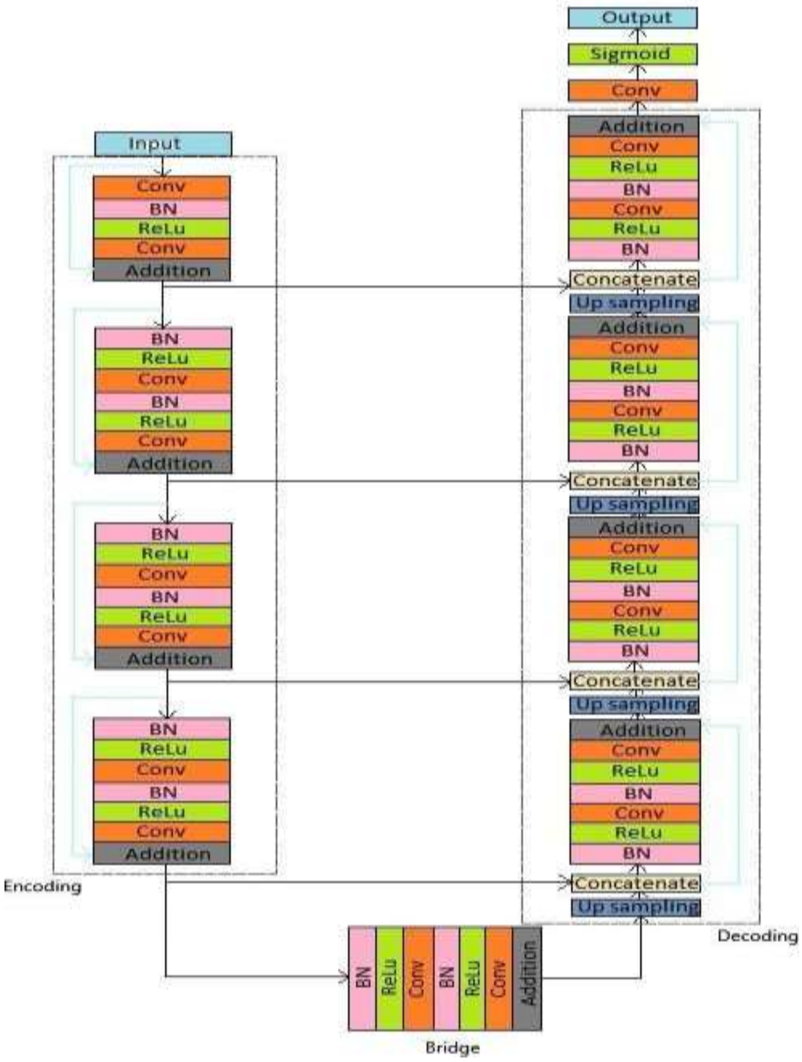

Fig. 1: Res-Unet-based segmentation model

We added one residual unit to each side i.e. encoder and decoder side of a base model for performance incrementation. After adding one residual unit, the model reached a saturation state, so adding more units was not desirable. The first part comprises an encoder that encodes input images into compact representations from the three parts of the network. The middle part works like a bridge connection between the encoder and decoder parts. And last part is the decoder part which recovers the representation to semantic segmentation. Identity mapping and 3X3 convolution layers were used to construct all three components. A BN layer, a ReLU activation layer, and a convolutional layer are all present in each convolution block. The unit's input and outputs are connected by the identity mapping. There are four residual units in the encoding path. Instead of using a pooling operation to lower the size of the feature map, each unit's first convolution block receives a stride of 2, which cuts the feature map in half. The decoding path has four residual units, much like the encoding path. The feature maps from the appropriate encoding route are concatenated with the feature maps from the lower level and up-sampled before each unit. The multi-channel feature maps are projected onto the necessary segmentation using a 1X1 convolution and a sigmoid activation layer after the last level of decoding. There are 19 convolutional layers in all.

3.3.3Training

The network is trained using the input images and the related segmentation masks. Different values and assignments were examined for the training learning rate, batch size, number of epochs, units, validation split, optimizer, loss function, and activation function. It had been done with a validation split of 0.20, a network batch size of 32, and 100 epochs.

3.3.4 Optimizer

The Adam Optimizer is a variation on the stochastic gradient descent (SGD) and root mean squared (RMSprops) algorithms [12]. It is a technique for effective stochastic optimization that just needs first-order gradients and uses little memory. It determines unique adaptive learning rates for each network parameter. The word "adaptive moment estimation" appears in its name. In this work, an Adam optimizer with a default learning rate of 0.001 was employed.

3.3.5Loss Function

Dice loss for Keras is smoothed to approximate a linear (L1) loss is used. It ranges from 1 to0 (no error), and returns results similar to binary cross-entropy. It is a common metric for pixel segmentation that can also be modified to act as a loss function. It’s calculated by the formula,

$$\text{Dice loss} = 1 - \text{DICE} \qquad (1)$$

Where, DICE is the evaluation metric Dice coefficient.

4 Results

4.1 Evaluation metrics

4.1.1Dice Coefficient

We used the Dice coefficient as an evaluation metric in experimentation. It is one of the most frequently used metrics in medical image segmentation. Lee R. Dice proposed it for ecological research. It calculates the degree to which two binary masks overlap. It is calculated by dividing the amount of overlap between the two segmentations by the combined size of the two objects. In this metric, the average size of their intersection is used to quantify the match between two sets.

$$\text{DICE} = 2|V_{ref} \cap V_{seg}|/|V_{ref}| + |V_{seg}| \qquad (2)$$

Where Vref is the set of voxels identified as foreground in the reference volume (ground truth) and Vseg is the set of voxels identified as foreground in the segmented volume. The total number of items in a set is indicated by the symbol |.|.

DICE has a value between 0 and 1. A flawless segmentation returns a value 1, whereas segmentation with no overlap of the reference and segmented picture foregrounds returns the value of 0.

Two different models with comparable architectures were utilized throughout the training. The first model was developed to partition the liver in abdominal CT images. The liver was separated from the abdomen MRI scan images using the second model. The masks of MRI data illustrated other abdominal organs as well. We implemented a python algorithm that mapped the liver to elucidate it. After the implementation of the model over 100 epochs on CT scans, we got desirable results, some of which are given in Fig. 2. The CT scanned images of the abdomen segmented liver accurately through the proposed model. The below figures show CT scan data, its ground truth image present in the dataset and the last row shows the segmentation results of the liver done by the model.

a)

b)

c)

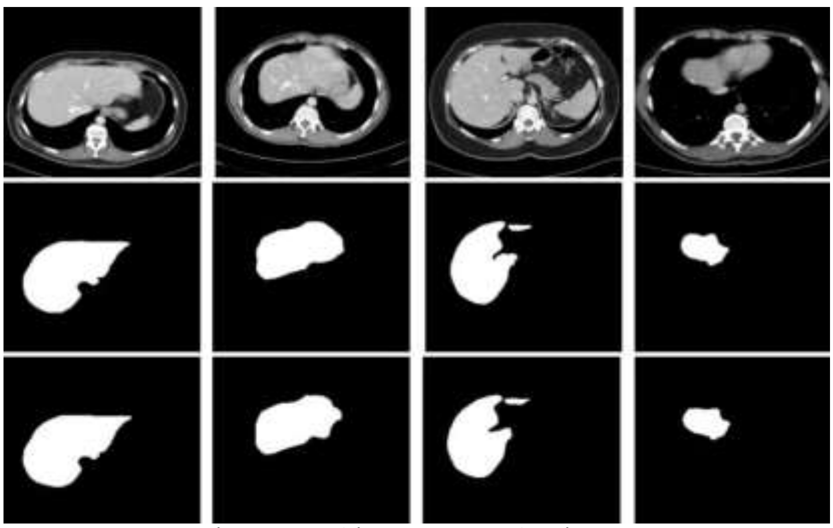

Fig. 2: CT Segmentation: a) CT Scans b) Ground Truths c) Liver Segmentation results

Similarly, the model was implemented for MRI scans, the MRI data of 647 images with their respective ground truths were trained for over 100 epochs on the proposed model to obtain the accurate segmentation of the liver from the abdomen. The results of MRI scans are in Fig. 3.

a)

b)

c)

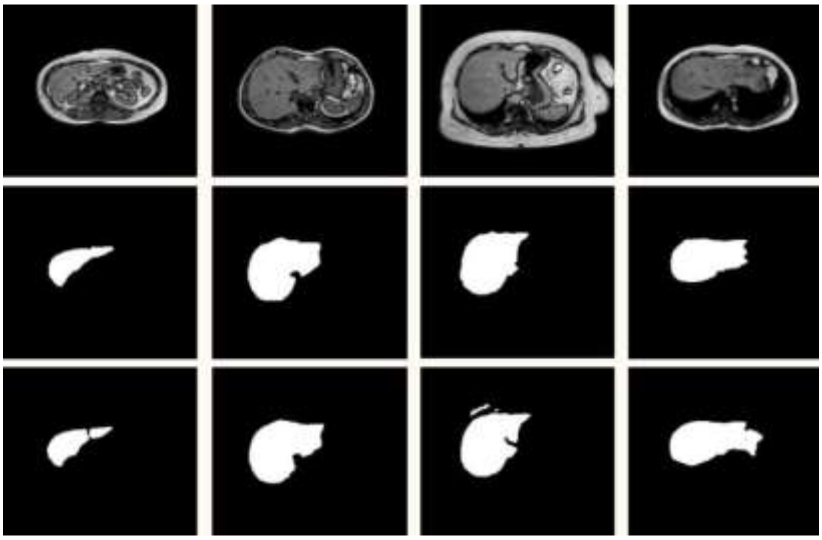

Fig. 3: MRI Segmentation: a) MRI scans b) Ground Truths c) Liver Segmentation results

We used the matplotlib python library to plot the model's performance and verify the integrity and correctness of the data. The network's model Dice coefficient and model Dice loss for liver segmentation from the abdominal CT scan and MRI scanned images were plotted respectively from Fig. 4 up to Fig. 7.

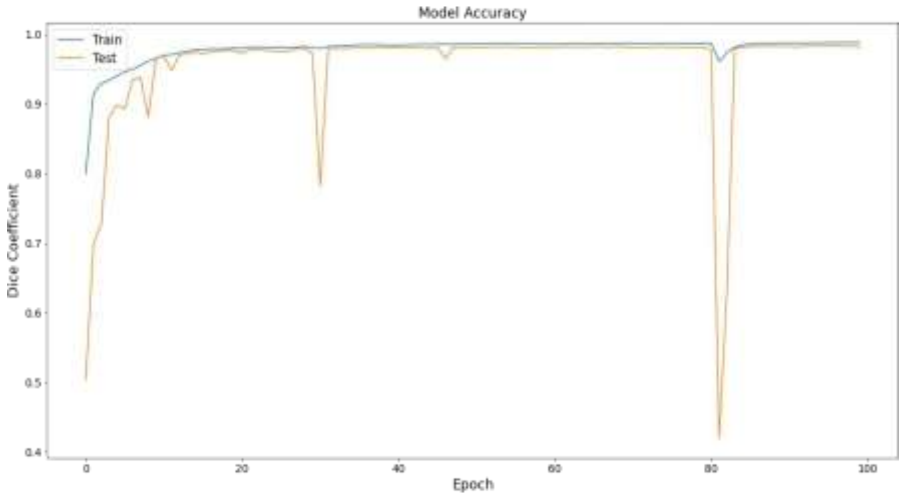

Fig. 4: Epoch vs dice coefficient in CT Image dataset

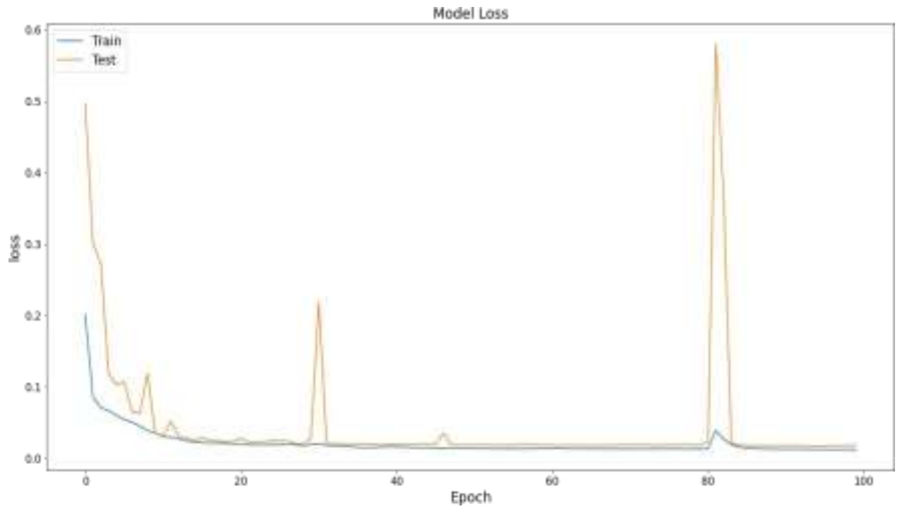

Fig. 5: Epoch vs dice loss in CT

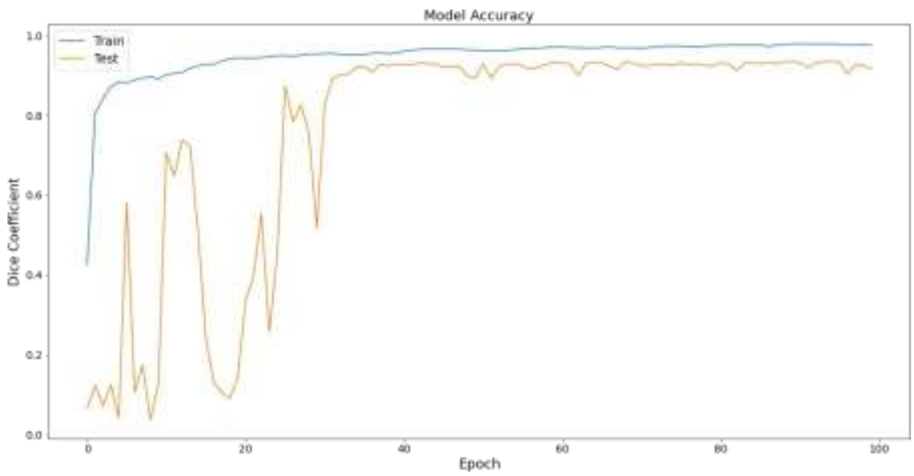

Fig. 6: Epoch vs dice coefficient in MRI image dataset

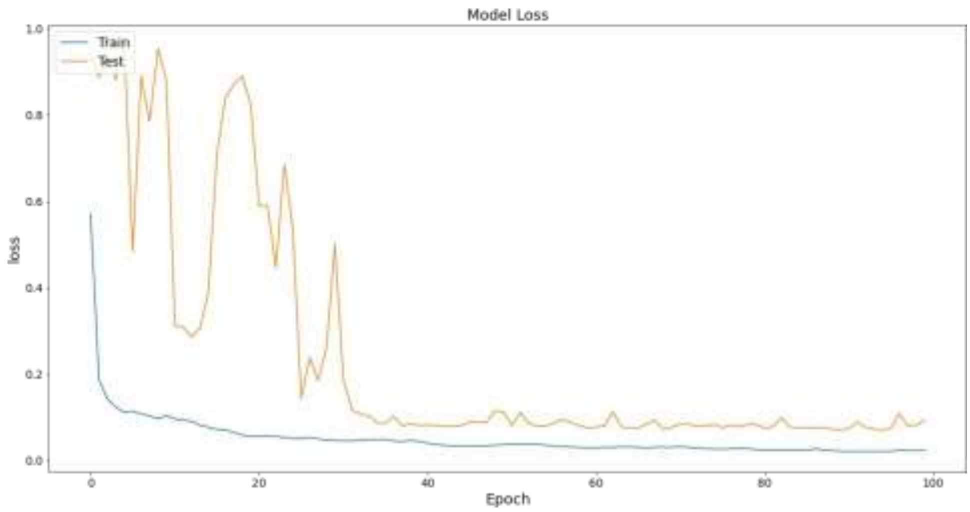

Fig. 7: Epoch vs dice loss in MRI

Table 2. Comparative analysis of different liver segmentation models

Sr. No.	Application	Modality	Segmentation Models	Dataset	Dice Coefficient	Proposed By
1.	Healthy Abdominal Organ Segmentation	CT	U-Net	CHAOS	0.980	PKDIA [19]
2.	Healthy Abdominal Organ Segmentation	CT	Dual Tail Net architecture	CHAOS	0.971	Median CHAOS1 [12]
3.	Healthy Abdominal Organ Segmentation	MRI	3D U-Net	CHAOS	0.869	ISDUE [12]
4.	Healthy Abdominal Organ Segmentation	MRI	U-Net module and hourglass network	CHAOS	0.905	Lachinov [12]
5.	Deep Learning-basedLiver Cancer Segmentation	CT	UNet architecture	3D-IRCADb- 01	0.96	Y. Abebe, Dr. K.Anlay and Mohammed A.[10]
6.	Proposed	CT	Res-Unet	CHAOS	**0.983**	Ours
7.	Proposed	MRI	Res-Unet	CHAOS	**0.935**	Ours

5 Discussion

During this work, we found that the model can produce correct liver segmentation results for CT and MRI fused data as well when trained on MRI data. The dataset we used for this work was for both CT and MRI scans and the MRI dataset has elucidated other abdominal partswith the liver such as left/right kidneys, and spleens. The added residual unit on the network performed better and produced more accurate results on the chosen dataset. This model can be further implemented for tumor classification and detection from segmented liver images which will be helpful for doctors and radiologists to accurately spot cancer in the targeted organs and for various liver surgeries and transplants.

6 Conclusion

In this work, a Res-Unet segmentation architecture was implemented by transfer learning for liver segmentation from abdominal CT and MR images from the CHAOS challenge dataset. For performance improvement, a base model's encoder and decoder sides one residual unit was added, by modifying the pre-trained network we obtained a dice coefficient of 0.983 and dice loss of 0.017 on segmentation of liver from CT images and a dice coefficient of 0.935 and dice loss of 0.065 on segmentation of liver from MRI. We got the best results in terms of dice coefficient and segmentation of the liver for the CT dataset compared with the results of other researchers. As a conclusion, we demonstrated that the performance of the open-source, deep learning framework outperformed the DL-based models in liver cancer auto-segmentation. For clinical usage, an auto-segmentation algorithm based on deep learning is thought to produce a fair level of accuracy and reproducibility. Deep learning-based auto-segmentation is anticipated to be beneficial in clinical practice, particularly in daily adaptive plans based on several imaging modalities.

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