An Enhanced Attention U-Net++ Architecture for Accurate Liver and Tumor Segmentation in MRI Images

SK. Roshna[1], Chiranjeevi Althi[2], Dr. T. Ramashri[3]
[1]M. Tech Scholar, Dept of ECE, SVU College of Engineering, S.V. University, Tirupati, AP, India
[2]Academic Consultant, Dept of ECE, SVU College of Engineering, S.V. University, Tirupati, AP, India
[3]Professor, Dept of ECE, SVU College of Engineering, S.V. University, Tirupati, AP, India
doi.org/10.64643/IJIRTV12I6-187852-459

***Abstract*—Computer-aided diagnosis and treatment planning require the proper liver and liver tumor segmentation in the magnetic resonance image (MRI) scans. However, the task is difficult due to irregular tumor boundaries, insufficient contrast between tumor and healthy tissues, and inconsistency in the quality of images. This study proposes a deep learning-based multi-label Attention U-Net++ architecture for liver and tumor segmentation. The first part of the workflow is a preprocessing pipeline which involves resizing, normalization, denoising and contrast enhancement to improve the image quality. Attention U-Net++ model incorporates skip connections and attention processes within a model to focus on the areas of tumor and maintain the liver boundaries. The presented framework was trained and tested on ATLAS MRI data with a Dice score of 0.93 on liver and 0.85 on tumor with an average accuracy of 99%. These findings prove that preprocessing and Attention and U-Net++ work together to greatly enhance segmentation performance and has good prospects in the computer-aided diagnosis and treatment planning.**

***Index Terms*—Attention U-Net++, Deep Learning, Liver Tumor Segmentation, Medical Image Analysis, MRI.**

I. INTRODUCTION

Liver tumors are among the most prevalent cancers and a major cause of deaths worldwide from cancer. According to the World Health Organization (WHO), hepatocellular carcinoma (HCC) is the most common kind of liver cancer, making up around 80% of all hepatic malignancies [2,3]. The early diagnosis is crucial in better planning of treatment and clinical management. Diagnosis of liver diseases involves Magnetic Resonance Imaging (MRI) because they are non-invasive and have better soft tissue contrast compared to other imaging techniques [2,4,11]. MRI offers distinct demarcation between normal liver tissue and tumor abnormal tissue areas making it the imaging technique of choice in tumor segmentation [4,11].

Convolutional neural networks (CNNs) have become dominant models in automated medical image processing due to recent advancements in deep learning [1,5]. Deep Learning architectures, namely U-Net and variants of it, which are used often for segmentation purposes [6,7,8]. To enhance feature extraction and multiscale representation, U-Net++ builds on top of U-Net by introducing layered skip connections [10]. Attention mechanisms complement this by focusing on relevant regions, rejecting background noise, and enhancing robustness to variability [8]. The Attention U-Net++ architecture using a combination of these two offers better segmentation of complicated structures including liver tumors [5,6,9].

The contributions include the following:

1. An end-to-end MRI scan preprocessing pipeline, comprising of normalization, denoising, CLAHE, sharpening and resizing.
2. A simultaneous liver and tumor segmentation Attention U-Net++ model [5,6].
3. Detailed estimation based on various measures such as Dice score, IoU, sensitivity and specificity and accuracy [5,6,9].
4. High segmentation accuracy and improved Dice scores of liver and tumor regions are proven by the results of the experiments [5,6,9].

In general, the developed framework is a solid, precise, and interpretable method of analyzing liver tumors in MRI images, as it will decrease the radiologists' burden and improve the prompt identification of liver tumors [2,4,6,11].

II. METHODOLOGY

2.1 Attention U-Net++

Attention U-Net++ architecture is a U-Net++ architecture with attention gates that combine multi-scale feature fusion and region selective learning. The combination allows the network to divide complex and irregular structures, including the liver tumors in MRI images, into the diagnostically meaningful regions but excluding the background noise to a minimum. The architecture scores better in Dice and IoU than U-Net++, proving the strength of the architecture in medical image segmentation scenarios.

2.2 Block Diagram

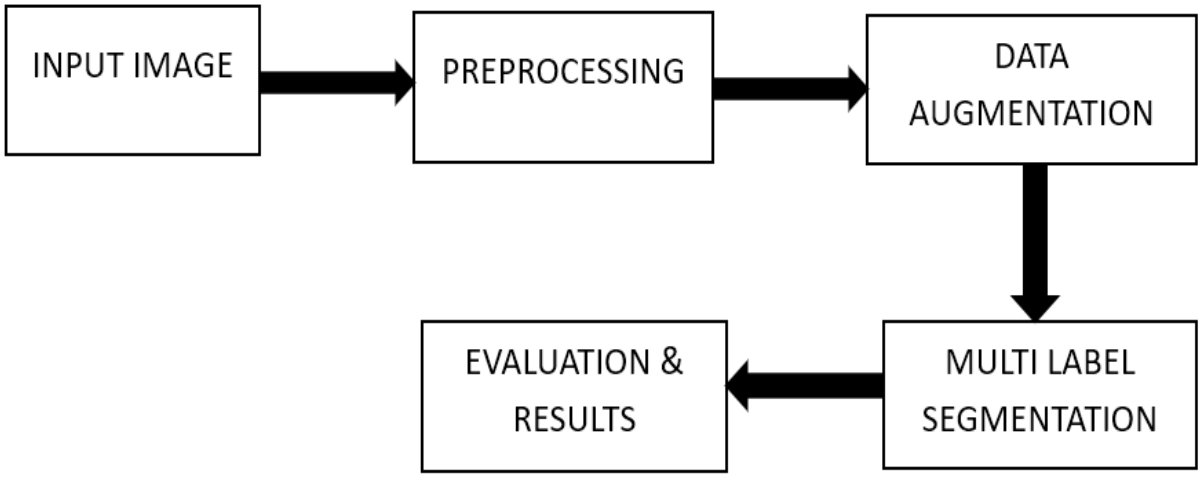


Figure 1: Block Diagram of the Proposed Method

2.2.1 Input Image

The dataset in the present study is the Automatic Tumor and Liver Segmentation (ATLAS) dataset, which is a publicly available benchmark dataset published as a part of the ATLAS challenge at the University of Burgundy. It has a total of 60 cases of contrast-enhanced T1-weighted MRI scans of patients with hepatocellular carcinoma (HCC). Training accounted for 70% of the dataset, followed by validation (15%) and testing (15%).

2.2.2 Preprocessing

To enhance the input image and offer consistent training, the following preprocessing steps were used:

2.2.2.1 Denoising - To prevent random noise Using a non-local means denoising filter, remove the edges.

2.2.2.2 Contrast Enhancement (CLAHE) -To emphasize tumor areas by enhancing local contrast.

2.2.2.3 Sharpening - A sharpening filter was used to bring out fine structural information especially tumor boundaries which is critical in accurate segmentation.

2.2.2.4 Resizing - All MRI slices were resized to 256 × 256 pixels equally to make sure that models could fit.

2.2.5 Z-score Normalization- Z-score normalization was applied to normalize intensity distribution between scans.

The above preprocessing processes made the tumors visible in a much better way, provided consistency throughout the dataset, and made the deep learning model trainable.

2.2.3 Data Augmentation

Data augmentation was performed using torchvision.transforms in PyTorch. Random horizontal and vertical flips, rotations of up to ±20 degrees, and brightness adjustments of ±10% were applied to enhance the model's generalization capability and reduce overfitting.

2.2.4 Multi-Label Segmentation Using Attention U-Net++

The Attention U-Net++ architecture is an advanced U-Net expansion that is used with the medical image segmentation, was used as the segmentation tool. In the model, multi-scale feature aggregation uses nested skip pathways and attention gates are used to focus on important areas and avoid background noise. This is especially useful in segmentation of liver tumors

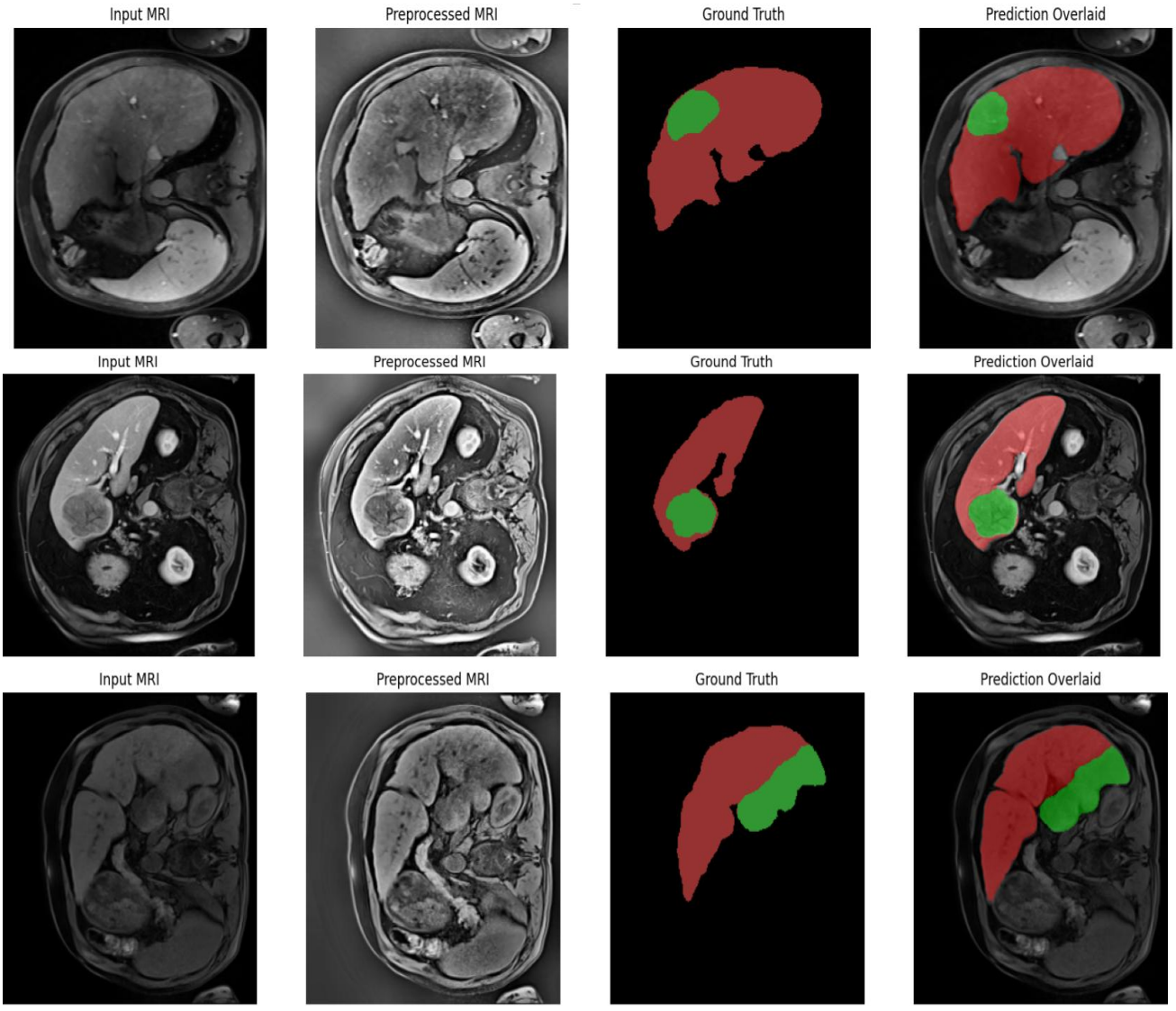
where the tumors are usually small, irregular and not contrasting with the surrounding tissues.

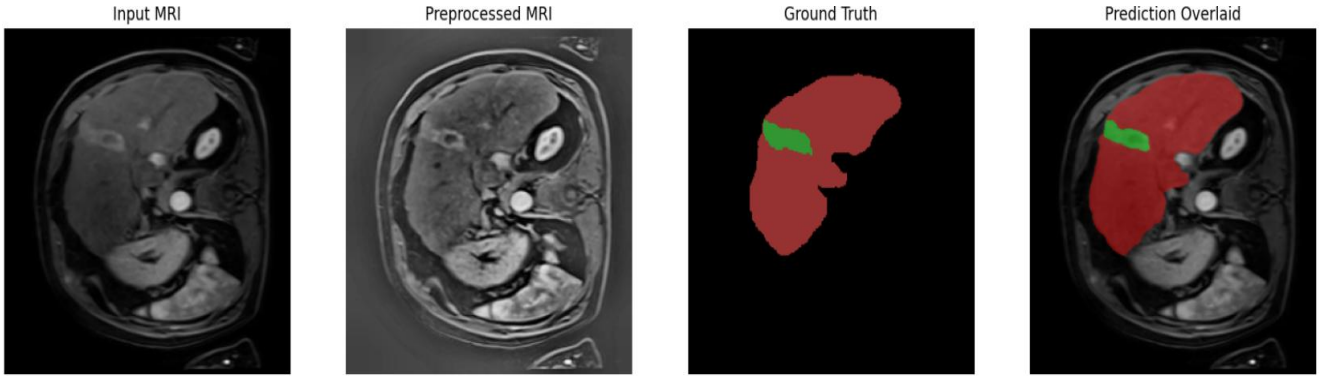
Multi-label segmentation was also trained on the network, and the liver and tumor domains were detected at the same time. Minimizing the pixel-wise classification issue was accomplished using the function is called Binary Cross Entropy with Logits Loss (BCEWithLogitsLoss). The value was optimized using the Adam optimizer using a 1 x 10^{-4} learning rate. Utilizing the Sigmoid activation function, the output layer generated probability maps for the tumor and liver segmentation classes. The Dice coefficient and pixel accuracy were calculated in liver and tumor during training.

III. RESULTS AND DISCUSSION

3.1 Qualitative Results

The output of segmentation is presented in figure 2. The model precisely outlines the liver and the tumor areas even with small tumors along the border.





(a) (b) (c) (d)

Figure 2: Qualitative Results of the Proposed Attention U-Net++ Model. Each row shows (A) Original MRI slice, (B) preprocessed image, (C) ground-truth image, and (D) predicted segmentation overlaid on original image (liver in red, tumor in green).

3.2 Evaluation Metrics

We used the following metrics to evaluate our Attention U-Net++ model's performance:

3.2.1 Dice Similarity Coefficient (DSC): The extent to which the ground truth resembles anticipated masks.

$$DSC=\frac{2|X\cap Y|}{|X|+|Y|}$$

Here, Y is the ground truth for mask predictions, while X is the segmentation mask prediction.

3.2.2 Sensitivity (Recall): The model sensitivity is its capability to correctly identify real positive pixels.

$$Sensitivity=\frac{TP}{TP+FN}$$

3.2.3 Specificity: The model is able to identify real negative pixels correctly.

$$Specificity=\frac{TN}{TN+FP}$$

3.2.4 Accuracy: Accuracy is used to determine the general percentage of pixels in the overall picture that were correctly categorized.

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

3.2.5 Intersection over Union (IoU): The gap between the ground truth and the expected segmentations may be found using IoU.

$$IoU=\frac{TP}{TP+FP+FN}$$

There are four potential outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

3.3 Quantitative Results

Attention U-Net++ model was tested on validation and test data sets in various measures: Dice score, IoU, sensitivity, specificity, accuracy and false positive rate (FPR). When tested on validation data for liver segmentation (a score of 0.9288) and tumor segmentation (a score of 0.8538), the model performed well.

Table 1: Measurements of the Proposed Model's Segmentation Performance

Metric	Liver	Tumor
Dice Score	0.9357	0.8518
Sensitivity	0.7267	0.8178
Specificity	0.9982	0.9992
IoU	0.7030	0.7848
Accuracy	0.9958	0.9973
FPR	0.0018	0.0008

As can be seen in Table 1, the proposed Attention U-Net++ provides large Dice and IoU values on both liver and tumor segmentation. The specificity of the liver (0.9982) and tumor (0.9992) are high, and the FPR is low, which verifies the ability of the network to distinguish tumor boundaries. Such measures suggest that the combination of attention modules is effective to improve attention to the corresponding areas and reduce the background noise.

3.4 Comparison with Existing Method

The results of contrasting the recommended Attention U-Net++ model with the conventional U-Net++ model are displayed in Table 2.

Table 2: Dice Results Comparison between the Baseline U-Net Plus and Proposed Attention U-Net Plus.

Metric	U-Net++ (Existing) [1]	Attention U-Net++ (Proposed)
Liver DSC	0.9220	0.9357
Tumor DSC	0.6870	0.8518

The given framework results in liver and tumor Dice score improvement. This contributes to the enhancement of the tumor especially since tumor zones are often minute and hard to capture.

IV. CONCLUSION AND FUTURE WORK

This paper details our efforts to enhance the Attention U-Net++ system for use in magnetic resonance imaging (MRI) liver and tumor segmentation. Nested skip connections with preprocessing, augmentation, and attention showed a high performance in comparison to baseline U-Net++. The model scored 0.93 when liver is involved and 0.85 when tumor is involved with a high specificity and a low rate of false positive. These findings prove the strength and appropriateness of the proposed framework to clinical workflows. To sum up, the suggested Attention U-Net++ model is an influential and feasible framework to the exact segmentation of liver and tumor on MRI images.

Despite the good results of the proposed Attention U-Net++ framework, it still has various ways of improvement. The application of the model to multi-class segmentation might be allowed to distinguish benign and malignant tumors and to provide the staging of the tumors. The use of 3D volumetric architectures could represent inter-slice relationships, and enhance spatial cohesion and contextual knowledge. It might also be examined in future research that employs multimodal imaging integration (e.g., MRI, CT, PET) in order to use complementary diagnostic data. In addition, real-time and lightweight models would be developed to help in deployment in the clinical environment. Lastly, it is necessary to validate the approach on larger and multi-centre data sets to make it robust and applicable across various populations.

REFERENCES

[1] J. Wang, Y. Peng, S. Jing, L. Han, T. Li, and J. Luo, "A deep-learning approach for segmentation of liver tumors in magnetic resonance imaging using UNet++," *Scientific Reports*, vol. 13, no. 9, pp. 1–12, 2023.

[2] World Health Organization, “Global cancer statistics 2020,” WHO, 2020. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cancer

[3] C. Ayuso, J. Rimola, R. Vilana, et al., “Diagnosis and staging of hepatocellular carcinoma (HCC): current guidelines,” *Eur. J. Radiol.*, vol. 101, pp. 72–81, Apr. 2018, doi: 10.1016/j.ejrad.2018.01.025.

[4] V. Chernyak, K. J. Fowler, A. Kamaya, et al., “Version 2018: Imaging of Hepatocellular Carcinoma in At-Risk Patients,” *Radiology*, vol. 289, no. 3, pp. 816–830, 2018, doi: 10.1148/radiol.2018181494.

[5] D. Said, G. Carbonell, D. Stocker, et al., “Semiautomated segmentation of hepatocellular carcinoma tumors with MRI using convolutional neural networks,” *Eur. Radiol.*, vol. 33, no. 9, pp. 6020–6032, 2023, doi: 10.1007/s00330-023-09613-0.

[6] T. Liu, J. Liu, Y. Ma, et al., “Spatial feature fusion convolutional network for liver and liver tumor segmentation from CT images,” *Med. Phys.*, vol. 48, no. 1, pp. 264–272, Jan. 2021, doi: 10.1002/mp.14585.

[7] P. L. Pham, C. Xu, and J. L. Prince, “Current methods in medical image segmentation,” *Annu. Rev. Biomed. Eng.*, vol. 2, pp. 315–337, 2000, doi: 10.1146/annurev.bioeng.2.1.315.

[8] S. Saumiya and S. W. Franklin, “Residual deformable Split Channel and spatial U-Net for Automated Liver and Liver Tumour Segmentation,” *J. Digit. Imaging*, Jul. 2023, doi: 10.1007/s10278-023-00874-1.

[9] D. T. Kushnure and S. N. Talbar, “MS-UNet: a multi-scale UNet with feature recalibration approach for automatic liver and tumor segmentation in CT images,” *Comput. Med. Imaging Graph.*, vol. 89, p. 101885, Apr. 2021, doi: 10.1016/j.compmedimag.2021.101885.

[10] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, “UNet++: Redesigning skip connections to exploit multiscale features in image segmentation,” *IEEE Trans. Med. Imaging*, vol. 39, no. 6, pp. 1856–1867, Jun. 2020, doi: 10.1109/TMI.2019.2959609.

[11] K. Bousabarah, B. Letzen, J. Tefera, et al., "Automated detection and delineation of hepatocellular carcinoma on multiphasic contrast-enhanced MRI using deep learning," *Abdom. Radiol.*, vol. 46, no. 1, pp. 216–225, Jan. 2021, doi: 10.1007/s00261-020-02604-5.