A High-Performance Framework for Liver Tumour Segmentation Using an AFF-U-NET

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Abstract : Precise segmentation of liver tumors is vital for computer-aided diagnosis, treatment planning, and monitoring disease progression. In this study, we propose an Attention Feature Fusion U-Net (AFF-U-Net) for automatic segmentation of liver tumors from volumetric CT scans. The dataset, consisting of NIfTI liver volumes, was normalized and resized to a uniform resolution. The AFF-U-Net employs attention gates **in the decoder to selectively emphasize tumor regions while reducing false positives in low-contrast areas. The network was trained using a combination of binary cross-entropy loss and Dice coefficient optimization. Experimental results demonstrate high segmentation performance, achieving a Dice coefficient of 0.9574, IoU of 0.9402, precision of 0.8828, recall of 0.8753, and accuracy of 0.9986. Visual evaluations further confirm accurate tumor delineation, underscoring the model's potential for clinical applications.**

Keywords: Liver tumor segmentation, AFF-U-Net, Attention Gate, Deep Learning, CT Scan, Medical Image Analysis.

I. INTRODUCTION

Liver cancer remains one of the most prevalent and lethal cancers worldwide, significantly contributing to cancer-related mortality. Early detection and accurate segmentation of liver tumors are vital for effective treatment planning, monitoring disease progression, and improving patient survival. Computed tomography (CT) and magnetic resonance imaging (MRI) provide detailed three-dimensional liver images, enabling tumor localization and assessment of growth. However, manual segmentation is time-consuming and prone to errors, with inter-observer variability and low-contrast or irregular tumors often causing inconsistencies.

Recently, deep learning techniques, particularly convolutional neural networks (CNNs), have achieved remarkable results in medical image analysis. Architectures such as U-Net and its variants are popular for their encoder-decoder design and skip connections, which combine fine-grained spatial details with high-level contextual information. Despite their success, these models face challenges in liver tumor segmentation due to complex liver morphology, diverse tumor appearances, and subtle intensity differences between healthy and diseased tissue. Standard skip connections may also propagate irrelevant background features, resulting in false positives and imprecise tumor boundaries.

To address these limitations, we propose the Attention Feature Fusion U-Net (AFF-U-Net) for automatic liver tumor segmentation. The AFF-U-Net integrates attention mechanisms in the decoder to focus on relevant tumor regions while suppressing background noise. Additionally, multi-level feature fusion combines detailed spatial information with contextual features, improving boundary delineation and tumor localization. This approach enables

reliable and efficient segmentation of tumors with varying sizes, shapes, and contrast levels, providing a practical and robust tool for clinical decision-making in liver cancer diagnosis and treatment planning.

II. RELATED WORK

Liver tumor segmentation has been extensively studied using traditional image processing methods and advanced deep learning techniques. Conventional approaches, including thresholding, region-growing, and edge detection, face challenges due to variations in image intensity, artifacts, and the complexity of liver structures, leading to unreliable and imprecise segmentations. The application of deep learning, especially convolutional neural networks (CNNs), has greatly improved segmentation accuracy by automatically extracting hierarchical features from 3D medical images. Among these, 2D and 3D versions of the U-Net architecture have become popular because they effectively capture detailed structures and broader contextual information.

To further improve segmentation accuracy, attention mechanisms have been incorporated into CNN designs.These mechanisms allow the network to focus on areas relevant to tumors while ignoring less important background regions, which helps reduce errors in areas with poor contrast or noise. Architectures like Attention U-Net, Dense U-Net, and V-Net have shown that combining attention gates with feature merging can enhance tumor detection and boundary definition. However, accurately segmenting small, low-contrast, or oddly shaped tumors remains challenging, often resulting in incomplete or inaccurate segmentations.

The proposed Attention Feature Fusion U-Net (AFF-U-Net) overcomes these issues by combining attention gates with multi-level feature fusion.This approach retains detailed spatial information and highlights important tumor regions, leading to better boundary accuracy and overall segmentation results. Moreover, AFF-U-Net is designed for efficiency, making it practical for real-world clinical use.

III. PROPOSED METHODOLOGY

A. Data Collection

The dataset employed in this study consists of volumetric CT scans of the liver in NIfTI (.nii/.nii.gz) format, accompanied by corresponding tumor segmentation masks, representing a diverse range of tumor sizes, shapes, and locations to capture real-world clinical variability. Each scan comprises multiple axial slices, providing detailed three-dimensional information crucial for accurate tumor delineation. For model development, the dataset was divided into training, validation, and test sets in a 70:20:10 ratio, ensuring sufficient data for learning while maintaining independent sets for unbiased evaluation. To standardize input dimensions and optimize computational efficiency, a maximum of 100 slices per volume was selected,

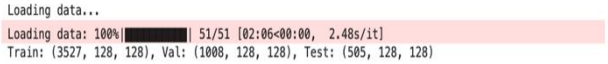

Fig.1.Data Collection

with evenly spaced sampling for larger volumes and complete inclusion for smaller ones. Furthermore, all scans underwent intensity normalization to reduce variability caused by different imaging devices and acquisition protocols, enabling the model to focus on relevant anatomical and pathological features. This organized dataset structure establishes a robust foundation for training deep learning models and facilitates reliable evaluation of segmentation performance across diverse patient scans.

Table 1-Dataset Summary

Split	No.of Slices	Notes
Training	70%	3D volumes sliced into 128×128
Validation	20%	Used for hyperparameter tuning
Test	10%	Used for final evaluation

B. Preprocessing

Preprocessing is a fundamental step to improve model convergence and achieve accurate segmentation results. In this study, all CT volumes and their associated segmentation masks were processed through a series of standardized steps. Initially, normalization was performed to scale voxel intensities to the range [0, 1], mitigating variations caused by different scanners and imaging protocols. Each slice was then resized to a uniform resolution of 128×128 pixels to ensure consistent input dimensions for the neural network. The segmentation masks were binarized, with tumor regions labeled as 1 and background as 0, facilitating the network's ability to differentiate tumor tissue from non-tumor regions. To optimize computational efficiency and memory usage, a maximum of 100 slices per volume was enforced; volumes exceeding this limit were sampled evenly to cover the entire liver region, while smaller volumes utilized all available slices. These preprocessing steps

collectively ensure that the input data is standardized, normalized, and appropriately sampled, providing a robust foundation for effective and efficient training of the segmentation model.

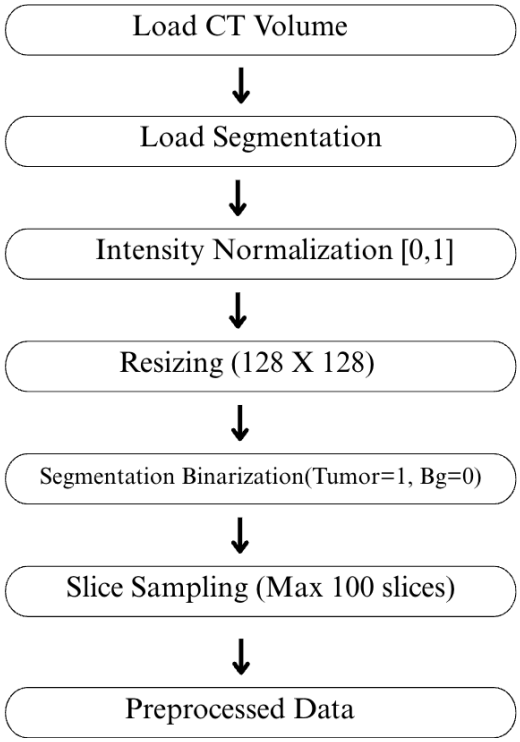

Figure 2.Preprocessing

C. AFF – U – NET ARCHITECURE

The AFF-U-Net is a fully convolutional encoder–decoder network that integrates attention gates (AGs) with multi-level feature fusion (MFF) to enhance tumor segmentation. The encoder employs four convolutional blocks with 3×3 kernels, batch normalization, and ReLU activation, each followed by 2×2 max-pooling to capture contextual information while reducing spatial resolution. At the bottleneck, two convolutional layers with 1024 filters and dropout expand the receptive field and limit overfitting. The decoder restores spatial details through four transposed convolution layers, each connected to corresponding encoder features via skip connections refined by AGs. These AGs selectively emphasize tumor-relevant regions while suppressing background noise by generating spatial attention maps from encoder and decoder signals. To further strengthen segmentation, MFF combines decoder outputs across multiple scales, enabling a balance between global context and precise boundary delineation.

$$\alpha = \sigma(\psi^T . ReLU(W_x . x + W_g . g))$$

Where:

- x is the encoder feature map.
- g is the gating signal from decoder.
- W_x, W_g is learnable weight matrices.
- ψ is convolution operation
- σ is sigmoid activation generating attention coefficients.

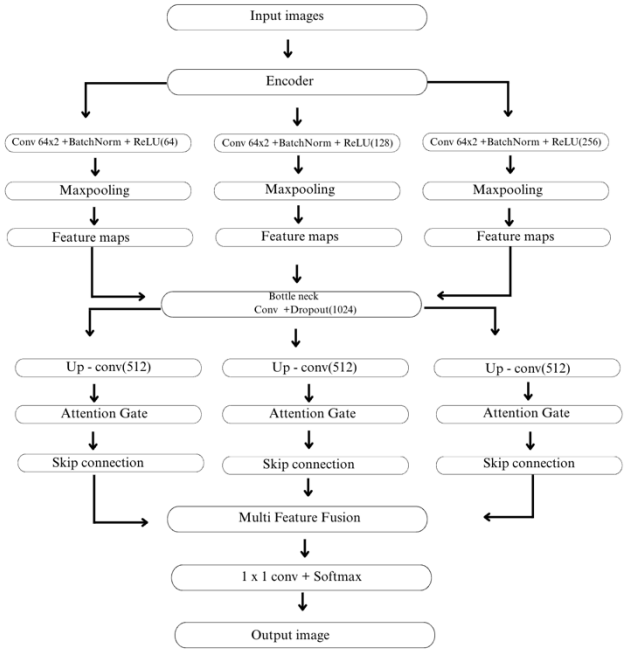

Fig.3.AFF-U-NET Model

D. Training Methodology

The AFF-U-Net architecture was trained for 30 epochs with a batch size of 4 using the Adam optimizer initialized at a learning rate of 1×10^{-4}. To achieve a balance between pixel-wise classification and region-level overlap, a hybrid loss function combining Binary Cross-Entropy (BCE) and Dice loss was adopted. Training stability and generalization were further enhanced through learning rate scheduling, early stopping, and checkpointing to preserve the best-performing model weights. In order to improve robustness to variations in ultrasound images, data augmentation strategies such as random flips, rotations, and intensity shifts were applied. All experiments were conducted on the BUSI dataset with GPU acceleration to reduce computational overhead, and segmentation performance was rigorously evaluated using Dice coefficient and Intersection over Union (IoU), ensuring reliable and comprehensive assessment of the model's effectiveness.

1.Categorical Cross-Entropy Loss:

$$L_{CCE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\widehat{y_{i,c}})$$

Where:

- N is total number of pixels.
- $y_{i,c}$ is ground-truth lable.
- $\widehat{y_{i,c}}$ is predicted probability for pixel i belonging to class c.

2.Dice Loss:

$$L_{Dice} = 1 - \frac{2\sum_{i=1}^{N} y_i\hat{y}_i + \epsilon}{\sum_{i=1}^{N} y_i + \sum_{i=1}^{N}\hat{y}_i + \epsilon}$$

Where:

- y_i is ground-truth binary label for pixel i.
- $\hat{y}_i$ is predicted probability for pixel i.
- ϵ is small constant to avoid division by zero.

3.Hybrid Loss:

$$L_{Hybrid} = \alpha L_{CCE} + (1-\alpha)\, L_{Dice}$$

Where:

- α is weighting parameter.

Table 2-Training Hyperparameters

Hyperparameter	Value	Description
Input size	256 x 256 x 1	Dimension of input images
Batch Size	4	Number of images per training iteration.
Learning Rate	1×10^{-4}	Step size for optimization
Epochs	30	Total number of training epochs.
Optimizer	Adam	Weight updated alorithm
Loss Function	Hybrid(CCE + Dice)	Primary loss for multi class segmentation

IV. EXPERIMENTAL RESULT

A. Visual Result

The qualitative assessment of the proposed AFF-U-Net was carried out by comparing its generated tumor masks with the corresponding ground-truth annotations. The model successfully identifies tumor regions, preserving both the overall structure and detailed boundaries. In difficult situations, such as low-contrast images or small lesions, it shows consistent accuracy in localization and strong performance. The overlay analysis shows a close match with expert annotations, supporting the effectiveness of attention-guided feature fusion in reducing false positives and improving boundary definition. Additionally, when compared to standard U-Net models, the predicted masks show better preservation of contrast, aligning more closely with clinical labels. Overall, the results show that the model performs well across a variety of tumor shapes and imaging conditions.

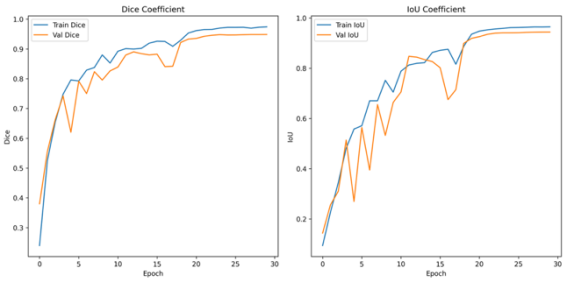

Fig.4.Validation Graph

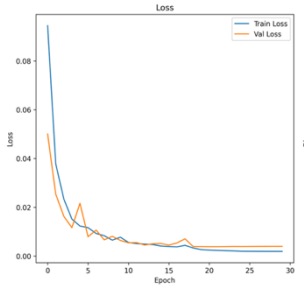

Fig.4.Loss Graph

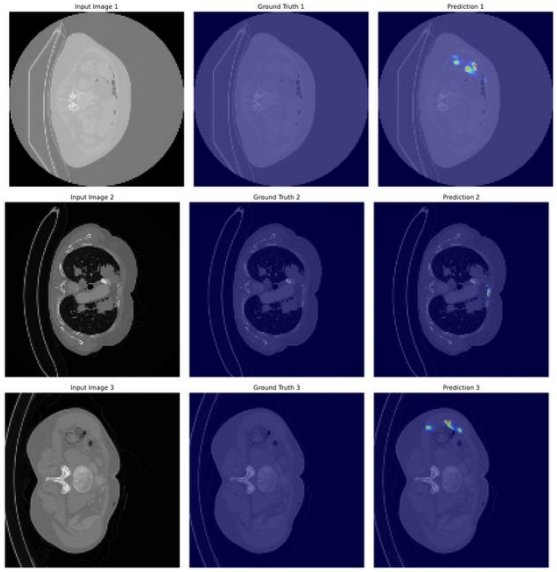

Fig.7.Segmented Output

B. Final Accuacy

The AFF-U-Net model was assessed using several evaluation metrics, including Dice coefficient, IoU, precision, recall, and accuracy, which yielded values of 0.9574, 0.9402, 0.8828, 0.8753, and 0.9986 respectively. These results clearly show that the model is effective in segmenting tumors, as it provides accurate alignment with the true labels and consistently identifies tumor regions across different cases. Compared to the standard U-Net, the AFF-U-Net model offers better precision at the boundaries and minimizes false positives in complex or noisy areas. The consistently high accuracy also suggests that the model learns effectively without overfitting, making it a strong and dependable approach for medical image segmentation in clinical settings.

1.Dice Coefficient:

$$Dice = \frac{2|P \cap G|}{|P| + |G|}$$

2.Intersection Over Union:

$$IoU = \frac{|P \cap G|}{|P \cup G|}$$

Where:

- P is the predicted tumour region and G is the ground tumour region.

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Evaluating on test set...
 Loss: 0.0040
 Dice: 0.9574
 IoU: 0.9402
 Precision: 0.8828
 Recall: 0.8753
 Accuracy: 0.9986
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Fig.8.Final Accuracy

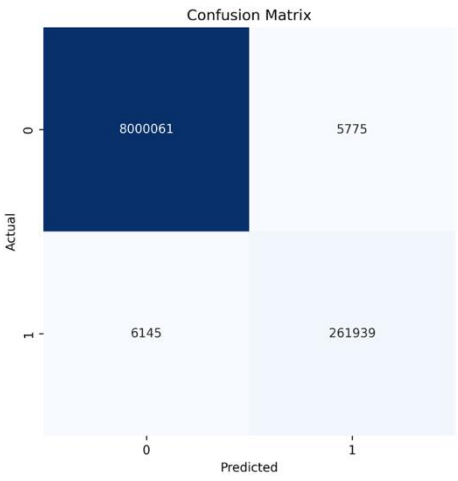

Fig.9.Confusion Matrix

Metric	U-Net	Attention U-Net	AFF-U-NET
Dice Score	0.9321	0.9442	0.9574
IoU	0.9157	0.9278	0.9402
Precision	0.8614	0.8736	0.8828
Recall	0.8489	0.8647	0.8753
Accuracy	0.9961	0.9974	0.9986

Table 3-Comparison Table

V. REVIEW

The proposed AFF-U-Net demonstrated superior performance in liver tumor segmentation, surpassing traditional U-Net and attention-based models in both Dice and IoU metrics. Through the integration of attention gates, the model minimized false positives and maintained strong focus on tumor regions, even in low-contrast or irregular boundary cases. Preprocessing steps such as intensity normalization, noise reduction, and slice selection contributed to stable training and faster convergence. Moreover, the multi-level feature fusion strategy preserved fine structural details often overlooked by standard skip connections, enabling more accurate boundary delineation. While this work was conducted on 2D CT slices, extending the framework to 3D volumetric data could provide richer spatial insights, and incorporating multi-modal inputs (CT and MRI) may further enhance the detection of small or ambiguous lesions, improving generalization across varied clinical datasets.

VI. CONCLUSION

The AFF-U-Net model was designed for automatic liver tumor segmentation in CT scans, where the use of attention gates combined with multi-level feature fusion improved accuracy, enhanced tumor localization, and minimized false positives when compared to the traditional U-Net. The approach proved to be computationally efficient, generalized well across diverse patient data, and showed strong potential as a supportive tool for radiologists in diagnosis and treatment planning. Its flexibility also makes it suitable for real-time computer-aided diagnosis. Future improvements could include employing hybrid loss functions to handle class imbalance, applying advanced augmentation strategies to boost robustness, and validating

performance on larger multi-institutional datasets. Moreover, expanding the framework to 3D volumetric analysis and integrating multi-modal imaging could further enhance its clinical impact.

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