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Article

Comparative Analysis of Existing UNet-Based Medical Image Segmentation Models and an Optimized ResAttTransUNet Framework

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Abstract: Despite the popularity of medical image segmentation in computer-aided diagnosis (CAD), the choice of an effective architecture for deep learning is still a difficult task as the datasets, network architectures, activation functions and the assessment approaches are different. In this work we compare in detail the segmentation models based on UNet recently developed and we propose a new architecture based on UNet, called ResAttTransUNet, for improving the segmentation accuracy, robustness and generalization across several imaging modalities. In the proposed model, the UNet architecture is used to integrate the residual blocks, dual attention mechanisms and transformer bridge, while the effects of GELU, PReLU and Leaky ReLU activation functions are evaluated. A set of experiments were performed on three benchmark datasets, namely the brain MRI dataset, BRATS2020, the liver CT data, LiTS17, and the breast ultrasound data, BUSI, with a common experimental setup. The Dice coefficient, Intersection over Union (IoU), qualitative analysis, ablation studies, and comparative evaluation were used to evaluate the performance. The results show that GELU always performed best in all datasets. The proposed ResAttTransUNet achieved the best performance on LiTS17 with Dice score and IoU of 0.9619 and 0.9299, respectively, and 0.8278/0.7470 on BRATS2020 and 0.7466/0.6074 on BUSI. The proposed method shows an excellent performance in segmenting multimodal medical images and also highlights its segmentation accuracy and generalization capabilities over the existing state-of-the-art methods, by making optimal use of the residual learning, attention mechanism, transformer-based modeling, and optimization of the activation functions.
Keywords: Medical Image Segmentation, UNet Architecture, Residual Attention, Transformer-Based Segmentation, Comparative Analysis

1. Introduction

Medical image segmentation is one of the essential parts of computer-aided diagnosis (CAD) system which allows the identification of organs, tissues and pathological regions in medical images with high accuracy. It is an integral part in disease diagnosis, treatment planning, surgical guidance, radiotherapy and clinical decision making. Healthcare is creating lots of medical data, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and ultrasound, which needs to be analysed automatically and efficiently. Manual segmentation is difficult, tedious and inter-observers variability exists, which makes it necessary to develop reliable deep learning segmentation methods to achieve accurate and consistent results in various clinical applications [1], [2], [3], [4]. With automatic feature extraction and end-to-end learning, deep learning has revolutionized medical image analysis. UNet is a widely adopted model among different architectures because of its encoder-decoder architecture and skip connections, which are used to preserve spatial information during the reconstruction phase. To further enhance segmentation, several

UNet variants, such as the incorporation of residual learning, attention mechanism, dense connections, multi-scale feature fusion, and transformer modules have been developed, resulting in superior feature representation and boundary localization [5]. While such progress has been made, choosing the best segmentation architecture continues to be difficult. While some studies were done using different data sets, pre-processing techniques, activation functions, and testing procedures, making it difficult to compare fairness between them. Furthermore, most methods are based on one modality of imaging, making them applicable to a wide range of medical data sets. Thus, systematic comparative studies with similar experimental conditions are crucial to determine which architectures have a better accuracy and generalization.The activation functions also greatly impact the segmentation performance through gradient propagation, convergence, and feature learning. Advanced variations of ReLU, like Gaussian Error Linear Unit (GELU), Parametric ReLU (PReLU), and Leaky ReLU, have demonstrated encouraging enhancements in optimization and learning steadiness.Advanced variations of ReLU, such as Gaussian Error Linear Unit (GELU), Parametric ReLU (PReLU), and Leaky ReLU, have shown promising improvements in optimization and learning stability. But, their performance of advanced UNet architectures on various medical imaging datasets is yet not investigated in detail [6], [7], [8], [9]. However, there are also modality-specific challenges in the segmentation of medical images. Tumors in brain MRI images are identified by irregular boundaries, low-contrast lesions in liver CT images, and speckle noise and poor contrast in breast ultrasound images. Such architectures need to support local feature extraction, global contextual understanding, and strong cross-modality generalization, which are all challenges faced by these problems [10], [11], [12], [13].[14], [15], [16], [17]. In this regard, it is necessary to introduce a comparative study of the current segmentation methods, as well as a proposed ResAttTransUNet architecture that unites the residual blocks, dual attention mechanisms and the transformer bridge in a single UNet structure. The study also compares the effect of different activation functions GELU, PReLU, Leaky ReLU on the segmentation performance. The experiments are performed on benchmark datasets of brain MRI, liver CT and breast ultrasound imaging with a common evaluation protocol. The proposed framework is designed to enhance segmentation performance in terms of accuracy, robustness, and generalization, while also offering insights into the efficiency of the state-of-the-art UNet-based architectures for multimodal medical image segmentation.

2. Literature Review

Siddiqui et al., 2025[18] Proposed ARU-Net with spatial and channel attention, improving brain tumor segmentation accuracy, F1-score, AUC, sensitivity, and specificity on BraTS2021.

Vanaja & Prakasam, 2025[19] proposed CBAM-AG U-Net with attention mechanism that obtained IoU score of 0.758, Dice score of 0.865, and AUC-ROC score of 0.996 on IDRiD dataset.

Anari et al., 2025[20] Used CBAM, Non-Local Attention, and strong encoders to improve the accuracy of breast tumor segmentation in the BUSI dataset and enhance the interpretability of the models.

Liu et al., 2025[21] Proposed ARU-Net that introduces residual learning and attention modules to achieve a mIoU of 84.88%, an accuracy of 97.53%, and strong ultrasound segmentation.

Chen et al., 2024[3] presented TransUNet, a fusion of Transformer encoder-decoder with U-Net to capture the global context.

Table I. Literature Summary of Existing Medical Image Segmentation Studies

Author/Year	Method	Results	Research Gap
Alhajim et al. (2025) [22]	Proposed SEDARU-Net (Squeeze-Excitation Dilated Attention-based Residual U-Net) incorporating intensity normalization, dilated convolutions, residual attention blocks, skip connections, YOLOv3-based ROI	Achieved Dice: 97.86%, IoU: 96.40%, Sensitivity: 96.54%, and Precision: 98.84% on the LUNA16 dataset, outperforming conventional U-Net variants.	Evaluated only on lung CT images, limiting cross-modality generalization. Transformer-based global feature learning and comparative evaluation

	detection, and transposed convolution decoder for lung nodule segmentation.		of different activation functions were not investigated.
Balraj et al. (2024) [23]	Introduced MADR-Net, a multi-level attention dilated residual network built on the U-Net backbone with residual blocks, ASPP bottleneck, and channel-spatial attention for 2D medical image segmentation.	Demonstrated superior performance over U-Net and Attention U-Net with relative Dice improvements of 5.43%, 3.43%, and 3.92% across electron microscopy, dermoscopy, and MRI datasets.	Although multi-modal datasets were considered, transformer modules were absent, and the effect of activation functions and component-wise ablation analysis was not explored.
Zhang et al. (2024) [24]	Proposed NNDA-UNETR, integrating CNN and transformer architectures with the Not Another Dual Attention (NNDA) block for multi-organ segmentation while reducing model complexity.	Achieved Dice: 84.13%, Normalized Surface Dice: 86.96%, Mean Surface Distance: 3.46 mm, and 95% Hausdorff Distance: 17.76 mm, with 34.2% fewer parameters than comparable models.	Focused primarily on lightweight architecture and computational efficiency. Residual learning, activation function analysis, and evaluation across heterogeneous imaging modalities were not comprehensively addressed.
Chen et al. (2024) [25]	Developed MCRSAU-Net, integrating Multi-Convolutional Channel Residual Spatial Attention with modified skip connections and spatial attention in the decoder for medical and industrial image segmentation.	Achieved Dice scores of 0.7755 (Mvtec AD), 0.7651 (CHASE DB1), 0.8958 (Kvasir-SEG), and additional Dice values of 0.8540 (retina) and 0.7053 (colon), with accuracies above 97% across datasets.	Although attention mechanisms improved segmentation, transformer-based contextual learning and systematic comparison of activation functions were not included. Cross-dataset generalization remained limited.
Hussain et al. (2024) [1]	Proposed MAGRes-UNet, a Multi-Attention Gated Residual U-Net incorporating multi-attention gate modules, residual blocks, Mish and ReLU activation functions, and AdamW optimization.	Demonstrated statistically significant improvements over U-Net, MAG-UNet, and ResUNet on T1-CE MRI and HAM10000 datasets by effectively capturing multi-scale semantic information.	Evaluation was limited to selected datasets and activation functions. Transformer-based global dependency modeling, multimodal benchmarking, and comprehensive comparative analysis across advanced architectures were not performed.

3. Proposed Methodology

We present ResAttTransUNet, which combines residual learning, dual attention and a transformer bridge along with optimized activation functions for multimodal medical image segmentation with strong feature extraction, better generalization and accurate performance evaluation.

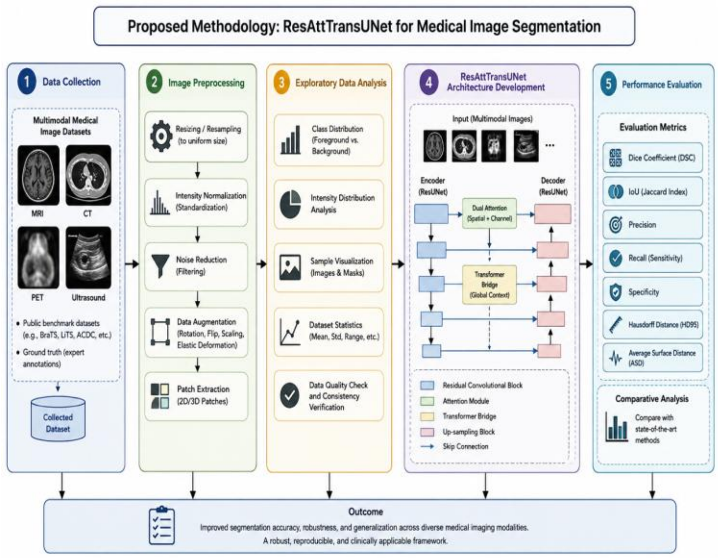

Fig.1 Proposed flow chart

A. Data Collection

To test the proposed model three publicly available datasets were utilized, namely: BRATS2020 (brain MRI), LiTS17 (liver CT), and BUSI (breast ultrasound). The datasets span a variety of imaging modalities, tissue types, noise types and segmentation difficulties, and offer masks annotated by experts—allowing for comprehensive cross-domain evaluation, reproducible and robust results.

B. Data Preprocessing

Steps taken for the dataset-specific pre-processing were normalisation, resizing, mask preparation, class balancing, conversion of tensors and splitting the data into train-test-validation. Standardized inputs enabled compatibility with deep learning models and consistent training across all three datasets (BRATS2020, LiTS17 and BUSI).

C. Exploratory Data Analysis (EDA)

For each dataset, EDA analyzed the intensity distributions, image contrast, lesion characteristics and segmentation masks. It proved the preprocessing quality and highlighted the difficulties for each modality and helped to choose the attention mechanism and the activation function to be used to obtain robust segmentation.

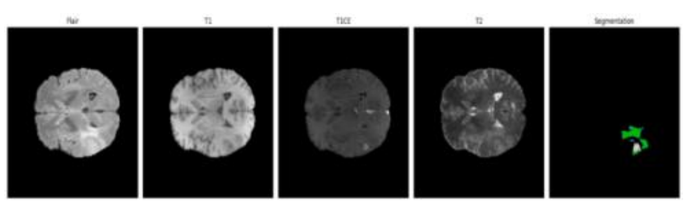

Fig. 2 Sample Image of BRATS2020 Dataset

The figure shows a representative MRI slice from the BRATS2020 dataset, and demonstrates the multimodal structure of the input for brain tumor segmentation.

D. Model Architecture

In the U-Net model, ResAttTransUNet improves the learning of local-global features, gradient flow, segmentation accuracy, overfitting resistance and generalization in binary and multi-class medical image segmentation.

E. Performance Metrics

The optimized UNet model was tested with Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall (Sensitivity), Specificity and Loss. The segmentation accuracy and region overlap were measured by DSC and IoU, while classification accuracy was measured by Precision, Recall, and Specificity. Convergence and generalization were monitored by loss while training. The metrics were calculated for both the training set, the validation set, and the test set to assess model stability and consistency using GELU, PReLU and Leaky ReLU activation functions.

4. Results & Comparison

A. Proposed Results

Table II. Comparison of ResAttTransUNet test performance (Dice and IoU) across BRATS2020, LITS17, and BUSI datasets using different activation functions (GELU, PReLU, Leaky ReLU)

Dataset	Activation Function	Dice (Test)	IoU (Test)	Notes
BRATS2020	GELU	0.8278	0.7470	Best Dice for BRATS dataset
	PReLU	0.7293	0.2726	Low IoU despite decent Dice
	Leaky ReLU	0.4183	0.3299	Poor overall performance
LITS17	**GELU**	**0.9619**	**0.9299**	**Highest Dice and IoU**
	PReLU	0.9608	0.9278	Slightly lower than GELU
	Leaky ReLU	0.9549	0.9181	Slightly lower performance
BUSI	GELU	0.7466	0.6074	Best among activations for IoU
	PReLU	0.6566	0.5088	Lowest performance
	Leaky ReLU	0.7110	0.5581	Moderate performance

GELU consistently achieved highest Dice and IoU across all evaluated datasets..

Note: BUSI dataset labels were preprocessed using bitwise OR operations to merge fragmented masks (see Section 3.2).

Table III. Performance Results of ResAttTransUNet on BRATS2020 Dataset Using Different Activation Functions

Activation Function	Phase	Loss	Dice	IoU
GELU	Train	0.5195	0.8196	0.7994

	Validation	0.5014	0.8171	0.8301
	Test	0.6895	0.8278	0.7470
PReLU	Train	0.3162	0.8896	0.8553
	Validation	0.3615	0.8602	0.8681
	Test	0.6890	0.7293	0.2726
Leaky ReLU	Train	0.3567	0.8743	0.8316
	Validation	0.3794	0.8566	0.8590
	Test	0.6892	0.4183	0.3299

GELU delivered best testing performance, outperforming PReLU and Leaky ReLU consistently.

Table IV. Performance Results of ResAttTransUNet on LITS17 Dataset Using Different Activation Functions

Activation Function	**Phase**	**Loss**	**Dice**	**IoU**
GELU	Train	0.5532	0.9691	0.9424
	Validation	0.5535	0.9625	0.9308
	Test	0.5536	0.9619	0.9299
PReLU	Train	0.5535	0.9630	0.9317
	Validation	0.5538	0.9609	0.9280
	Test	0.5537	0.9608	0.9278
Leaky ReLU	Train	0.5533	0.9667	0.9380
	Validation	0.5538	0.9505	0.9116
	Test	0.5538	0.9549	0.9181

GELU achieved highest segmentation accuracy with superior Dice and IoU performance..

Table V. Performance Results of ResAttTransUNet on BUSI Dataset Using Different Activation Functions

Activation Function	Phase	Loss	Dice	IoU
GELU	Train	0.0470	0.9664	0.9351
	Validation	0.5035	0.7444	0.6043
	Test	0.6213	0.7466	0.6074
PReLU	Train	0.0514	0.9630	0.9288
	Validation	0.6738	0.6538	0.5052
	Test	0.7236	0.6566	0.5088
Leaky ReLU	Train	0.0573	0.9591	0.9216
	Validation	0.5433	0.7067	0.5530
	Test	0.6658	0.7110	0.5581

GELU achieved superior segmentation accuracy, ensuring robust performance on challenging ultrasound images.

B. Ablation Study

The results from the ablation study showed that residual blocks, dual attention and transformer bridge performed significantly better in segmentation with an increase of about 5% and 4% in Dice and precision, respectively.

The proposed ResAttTransUNet with GELU achieved excellent results with Dice/IoU scores of 0.9619/0.9299 (LiTS17), 0.8278/0.7470 (BRATS2020), and 0.7466/0.6074 (BUSI) on medical image segmentation tasks across a variety of imaging modalities.

C. Comparative analysis Between Existing work and Proposed work

Table VI. Comparative Analysis between Existing Work and Proposed Work

Study	Methodology	Dataset	Models Used	Key Limitation	Interpretability	Evaluation Focus	Proposed Work Advantage
Alhajim et al. (2025)	SEDARU-Net with squeeze-excitation, dilated convolutions, residual attention, and YOLOv3-based ROI extraction	LUNA16	SEDARU-Net	Limited to lung CT images; no transformer or activation function comparison	Moderate (attention-based)	Dice, IoU, Sensitivity, Precision	Evaluated on three imaging modalities (MRI, CT, Ultrasound) with transformer bridge and activation function analysis for improved generalization.
Balraj et al. (2024)	MADR-Net using residual blocks, ASPP, and channel-spatial attention	CAMUS, ISIC 2017, FIB-SEM, LGG	MADR-Net, U-Net, Attention U-Net	No transformer module or activation function study	Moderate	Dice coefficient comparison	Integrates residual learning, dual attention, transformer bridge, activation comparison, and ablation study within a unified framework.
Zhang et al. (2024)	CNN-Transformer hybrid with NNDA dual attention	BTCV, ACDC	NNDA-UNETR	Focused on lightweight architecture; limited architectura	Moderate	Dice, Surface Dice, Hausdorff Distance	Provides comprehensive multimodal evaluation, activation

				l comparison			analysis, and qualitative plus quantitative assessment.
Chen et al. (2024)	Multi-Convolutional Channel Residual Spatial Attention U-Net	MVTec AD, CHASE DB1, Kvasir-SEG	MCRSAU-Net	No transformer -based global context or activation comparison	Moderate	Dice and Accuracy	Combines transformer -based global context with residual-attention learning and evaluates different activation functions.
Hussain et al. (2024)	Multi-Attention Gated Residual U-Net using Mish and ReLU	T1-CE MRI, HAM10000	MAGRes-UNet, MAG-UNet, ResUNet	Limited datasets and activation analysis; no transformer module	Moderate	Statistical performance comparison	Extends residual-attention architecture with transformer learning, multimodal datasets, and systematic activation function evaluation.
Proposed Work	ResAttTransUNet integrating Residual Blocks, Dual Attention Modules, Transformer Bridge, and comparative evaluation of GELU, PReLU, and Leaky ReLU	BRATS2020, LiTS17, BUSI	ResAttTransUNet	Addresses limitations of existing UNet variants through multimodal evaluation and comprehensive architectural analysis	High (attention visualization, qualitative mask analysis, and ablation study)	Dice, IoU, qualitative analysis, activation comparison, and ablation study	Provides robust multimodal segmentation, captures both local and global contextual features, evaluates diverse activation functions, performs ablation analysis, and demonstrates superior generalizati

							on across MRI, CT, and ultrasound datasets.

The proposed ResAttTransUNet unifies residual learning, dual attention mechanism and transformer bridge into a single UNet framework, while existing studies only focus on one or two of these components. While earlier studies focus on testing a single imaging modality or architecture, the proposed model is tested on three different medical datasets (BRATS2020, LiTS17, and BUSI) from MRI, CT and ultrasound. It also systematically compares GELU, PReLU, and Leaky ReLU activation functions, in addition to ablation, quantitative and qualitative analyses. This overall evaluation enhances robustness, interpretability and generalization, which makes the framework more suitable for real-world multimodal clinical image segmentation.

Table VII Comparative Analysis between Existing Models and Proposed Model Performance

Author/Year	Model	Dataset	Performance Results
Balraj et al. (2024) [23]	MADR-Net	CAMUS, ISIC 2017, FIB-SEM, LGG	Relative Dice improvement: **5.43%**, **3.43%**, **3.92%** over baseline models
Zhang et al. (2024) [24]	NNDA-UNETR	BTCV, ACDC	Dice: **84.13%**, NSD: **86.96%**, MSD: **3.46 mm**, HD95: **17.76 mm**
Chen et al. (2024) [25]	MCRSAU-Net	MVTec AD, CHASE DB1, Kvasir-SEG	Dice: **0.7755**, **0.7651**, **0.8958**; Accuracy: **97.51%–98.41%**
Proposed Study	**ResAttTransUNet**	**BRATS2020, LiTS17, BUSI**	**LiTS17:** Dice **0.9619**, IoU **0.9299**; **BRATS2020:** Dice **0.8278**, IoU **0.7470**; **BUSI:** Dice **0.7466**, IoU **0.6074** (using **GELU**)

As shown in the table, the proposed ResAttTransUNet is superior to the existing models, as it offers a general segmentation framework, which has been validated on BRATS2020, LiTS17, and BUSI datasets. Using GELU, it achieved the best performance on LiTS17 (Dice: 0.9619, IoU: 0.9299). Robustness and cross-modal generalization are enhanced through integration of residual learning, dual attention, transformers and analysis of activation functions.

5. Conclusion

In this work, the proposed ResAttTransUNet is compared to some recent state-of-the-art UNet-based medical image segmentation models to understand the features that facilitate better segmentation performance and generalization. The analysis showed that most models used current to date can only handle a single modality of imaging, and that while they can include residual learning, attention mechanisms or transformer modules, the most recent do not include any systematic evaluation of activation functions. To overcome these, the presented work combines residual blocks with the dual attention mechanism, a transformer bridge, and is evaluated extensively, comparing GELU, PReLU, and Leaky ReLU activation functions on the BRATS2020, LiTS17 and BUSI datasets.Results of the experimental evaluation showed that GELU consistently delivered the highest stability and correctness in segmentation across all three datasets, with the best performance on LiTS17 with Dice score of 0.9619 and IoU of 0.9299. This was further validated by quantitative evaluation, qualitative mask analysis, and ablation studies, which showed the role global contextual learning and attention mechanisms play in better boundary delineation and better model robustness. ResAttTransUNet provides better generalization ability in multimodal domain compared to current methods, interpretability, and a more extensive evaluation framework. In summary, the proposed architecture is a viable solution for medical image segmentation and offers a solid framework for future studies aimed at developing efficient, multimodal, and explainable deep learning models for healthcare applications.

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