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SEGMENTATION OF SUBARACHNOID HEMORRHAGE ON BRAIN CT IMAGES USING U-NET AND ATTENTION U-NET: A COMPARATIVE ANALYSIS

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Abstract

Subarachnoid Hemorrhage (SAH) is a critical medical condition involving bleeding into the subarachnoid space, often caused by aneurysmal rupture or trauma. Prompt and accurate diagnosis is essential to avoid severe neurological damage. This study compares two deep learning architectures—U-Net and Attention U-Net—for automated segmentation of SAH on brain CT scan images. Both models were trained and tested using a publicly available CT dataset, and evaluated using Dice Score, Intersection over Union (IoU), Precision, Recall, and F1 Score. The Attention U-Net achieved a Dice Score of 0.896 and IoU of 0.877, outperforming the standard U-Net which scored 0.867 and 0.848 respectively. While U-Net yielded higher precision (0.726), it showed more conservative segmentation behavior and lower recall. Visual inspection of segmented masks confirmed that the Attention U-Net was better at capturing small or low-contrast hemorrhagic regions. These findings demonstrate the effectiveness of attention mechanisms in improving spatial sensitivity and segmentation quality, indicating its potential in real-time neuroimaging diagnostic systems.

Keywords: *Subarachnoid Hemorrhage, Brain CT Scan, Medical Image Segmentation, U-Net, Attention U-Net, Dice Score*

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1. INTRODUCTION

Subarachnoid Hemorrhage (SAH) is a life-threatening neurological disorder characterized by bleeding into the subarachnoid space, most commonly caused by the rupture of a cerebral aneurysm or severe head trauma [1]. SAH accounts for approximately 5% of all strokes and affects between 2 to 25 individuals per 100,000 person-years in adults over 35 years of age, with a higher prevalence among females [1], [2]. Due to its sudden onset and potentially devastating consequences—including coma, long-term disability, or death—early and accurate identification is critical to improving clinical outcomes [3].

Computed Tomography (CT) is the most widely used imaging modality for initial SAH assessment, primarily because of its rapid acquisition, non-invasiveness, and high sensitivity to acute hemorrhage during the first 72 hours [4]. However, interpretation of CT scans relies heavily on the expertise of radiologists and is prone to subjectivity. Manual segmentation of hemorrhagic areas can be time-consuming, suffers from inter-observer variability, and is particularly challenging when segmenting low-contrast or small-volume hemorrhages [5], [6]. These limitations highlight the pressing need for automated, reproducible, and efficient tools for hemorrhage localization and delineation to support clinical workflows.

In recent years, deep learning-based approaches have revolutionized medical image analysis, particularly in semantic segmentation tasks using convolutional neural networks (CNNs). A comprehensive review by Litjens et al. reinforces this trend by highlighting how deep learning has advanced various medical imaging tasks, including detection, classification, and segmentation [7]. Among them, U-Net has emerged as a benchmark architecture due to its encoder–decoder structure and skip connections, which facilitate both global context and fine-detail localization [8]. While effective in many applications, standard U-Net architectures often struggle to segment small or diffuse lesions, such as SAH, where the boundaries between hemorrhagic and healthy tissues can be subtle and poorly defined [9].

Recent advances in deep learning have also focused on improving segmentation accuracy through semi-supervised learning and transfer learning approaches [10]. However, these methods often require extensive computational resources or pre-trained encoders, making lightweight architectures like U-Net and its attention-based variants attractive for practical deployment.

Moreover, attention-based models, originally popularized by Vaswani et al. in natural language processing [11], have shown strong potential in biomedical image segmentation by enabling models to focus on anatomically relevant regions while ignoring irrelevant background [12], [13]. Attention U-Net introduces attention gates (AGs) at skip connections to dynamically filter non-salient features and highlight clinically significant areas, improving performance on small or ambiguous hemorrhagic regions. Recent studies such as Yang and Jin [14] further support this by demonstrating the effectiveness of self and cross attention mechanisms in improving segmentation accuracy in complex CT imaging scenarios. Attention mechanisms are particularly advantageous in scenarios involving complex anatomical variation or ambiguous image intensities, where standard convolutional models often fail to prioritize subtle but clinically important regions [12].

This study aims to systematically compare the segmentation performance of U-Net and Attention U-Net models for delineating SAH regions in brain CT images. Both models are trained and validated on a publicly available dataset containing labeled hemorrhagic regions. Performance is evaluated using standard metrics—Dice Similarity Coefficient (DSC) and Intersection over Union (IoU)—alongside qualitative visual analysis. Furthermore, basic data augmentation and preprocessing strategies are employed to improve model generalization and training stability [1]. This research addresses the question: to what extent can attention mechanisms improve the segmentation of SAH in challenging, low-contrast CT imaging conditions?

2. RESEARCH METHOD

This study was conducted through several key stages, including data preparation, model architecture design, training procedure, and performance evaluation. The research methodology workflow used in this study can be represented by Figure 1.

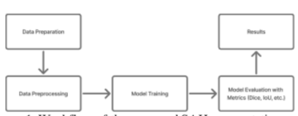

Figure 1. Workflow of the proposed SAH segmentation system using U-Net and Attention U-Net.

2. 1 Dataset Preparation

The dataset used in this study was sourced from a publicly available collection of annotated brain CT scans. Each image was paired with a binary segmentation mask that spatially outlines subarachnoid hemorrhage (SAH) regions. An example of the input–output pair is shown in Figure 2.

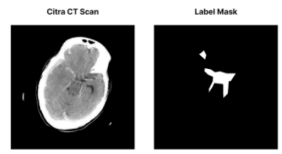

Figure 2. CT scan image and corresponding binary label mask

The dataset was split into three subsets: training, validation, and testing. The training set was used to learn model parameters, the validation set to monitor performance during training, and the test set to assess model generalization. Stratified sampling was applied to preserve class distribution across subsets.

2. 2 Data Preprocessing

Preprocessing was performed via a custom dataset class that automatically loads image–mask pairs. CT images were loaded in grayscale using OpenCV, resized to 256×256 pixels using bilinear interpolation, while masks were resized with nearest-neighbor interpolation to maintain binary fidelity [5], [9]. Pixel values were normalized to the [0,1] range by dividing by 255. Masks were binarized with a threshold of 0.5. Both images and masks were converted into PyTorch-compatible tensors with shapes [1, H, W]. This preprocessing pipeline was integrated directly into the DataLoader to enhance training efficiency and ensure reproducibility, following the design described by El Abassi et al. [13]. In addition, basic data augmentation techniques such as horizontal flips and random rotation were applied during training to enhance model robustness and reduce overfitting, in line with standard practices in medical image analysis [1], [15].

2. 3 Model Architecture

Two semantic segmentation architectures were implemented: U-Net and Attention U-Net. U-Net consists of a symmetric encoder–decoder structure with skip connections that help preserve spatial features. The encoder was enhanced using ResNet34 as a backbone to improve feature representation via residual learning, which also aids gradient stability and convergence during training [8].

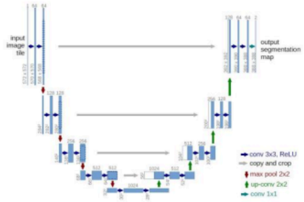

Figure 3. U-Net architecture adopted from [8].

Attention U-Net introduces attention gates (AGs) at skip connections between encoder and decoder paths. These gates learn to filter irrelevant spatial features and focus on salient regions related to the target structure (SAH). This design improves sensitivity to small and low-contrast regions by dynamically weighting relevant activations [12]. Figures 3 and 4 illustrate both architectures.

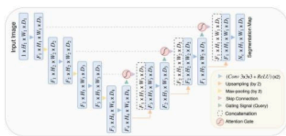

Figure 4. Attention U-Net architecture adapted from [12]

2. 4 Training Procedure

Model training was conducted under a supervised learning framework. Each input consisted of a grayscale CT image, with the ground truth being its corresponding binary mask. A compound loss function combining Binary Cross Entropy (BCE) and Dice Loss was used to capture both pixel-wise accuracy and spatial overlap. The Adam optimizer was employed with an initial learning rate of 1e-4. Training was conducted for 50 epochs with a batch size of 16. Validation was performed at the end of each epoch, and the best-performing model on the validation set was saved for final testing.

2. 5 Evaluation Metrics

The segmentation results were quantitatively evaluated on the test set using five metrics: Dice Score, Intersection over Union (IoU), Precision, Recall, and F1 Score. Dice Score measures spatial overlap between the predicted and ground truth masks, and is computed using Formula 1.

$$Dice = \frac{2\,x\,(|P \cap G|)}{(|P| + |G|)} \tag{1}$$

Intersection over Union (IoU) quantifies the agreement between prediction and ground truth masks relative to their union, and is defined by Formula 2.

$$IoU = \frac{(|P \cap G|)}{(|P \cup G|)} \tag{2}$$

Where P is the predicted binary mask, and G is the ground truth mask. These metrics provide comprehensive insight into segmentation accuracy, robustness, and consistency.

3. RESULT AND DISCUSSION

3. 1 Dataset Preparation

The visualization of training dynamics for both model architectures—U-Net and Attention U-Net—demonstrates that convergence was achieved within a relatively efficient training period. The trends observed in both training and validation loss curves exhibit consistent reductions, indicating that the models did not experience significant overfitting during the learning phase.

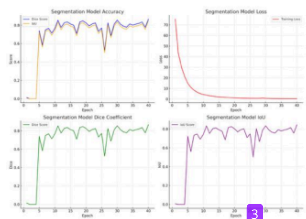

Figure 5. Training performance visualization of the U-Net model

As depicted in Figure 5, the U-Net model shows a rapid and stable decline in both training and validation loss starting from the early epochs. The convergence behavior appears consistent, with a minimal discrepancy between the training and validation losses, reflecting the model's capability to generalize well on unseen data.

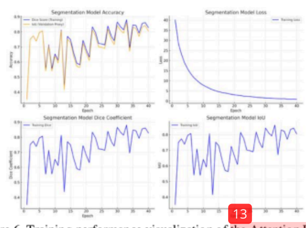

Figure 6. Training performance visualization of the Attention U-Net model

Conversely, the Attention U-Net model (Figure 6) reveals more fluctuation in loss values during the initial training phase and requires a longer duration to attain stabilization. Nevertheless, the later epochs indicate a convergence trajectory similar to that of U-Net, affirming that despite its increased architectural complexity, the optimization process remains effective.

Overall, both models exhibit stable and reliable convergence behaviors. The U-Net architecture demonstrates faster stabilization, whereas Attention U-Net, although slower to stabilize, ultimately aligns to a consistent performance pattern. These results indicate that both segmentation models possess adequate learning capacity and robustness in training for SAH segmentation tasks.

3. 2 Segmentation Output Visualization

To illustrate the spatial performance of both models, Figure 7 presents segmentation results from three representative brain CT scan samples. Each row displays a sample composed of four columns: the original CT scan with ground truth annotation (red contour), the prediction map from the U-Net model, the prediction map from the Attention U-Net model, and the binary ground truth mask for comparison.

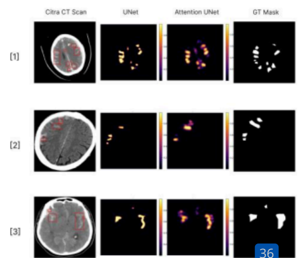

Figure 7. Visual comparison of segmentation results by U-Net and Attention U-Net models

In the first sample, U-Net successfully detected most of the hemorrhagic region with a Dice Score of 0.59 and IoU of 0.42. The Attention U-Net achieved a slightly higher Dice Score of 0.61 and IoU of 0.44, along with a Recall of 0.69, indicating improved sensitivity in capturing the target area.

In the second sample, where the SAH region was smaller, U-Net produced high precision (0.70) but low recall (0.31). Attention U-Net improved recall to 0.44 and Dice Score to 0.49 (compared to U-Net's 0.43), demonstrating its advantage in identifying small, localized structures. In the third sample, both models produced consistent predictions. U-Net recorded a Dice Score of 0.67 and IoU of 0.51, while Attention U-Net outperformed with a Dice Score of 0.73 and IoU of 0.57. These findings suggest that although both models approximate the ground truth with high accuracy, Attention U-Net consistently maintains better metric balance.

Overall, the combined visualizations in Figure 7 indicate that U-Net excels in broader region coverage, whereas Attention U-Net demonstrates superior spatial accuracy and sensitivity, especially in identifying smaller and more diffuse SAH regions.

3. 3 Quantitative Performance Evaluation per Sample

Table 1 presents the quantitative evaluation results based on six primary metrics: Dice Score, Intersection over Union (IoU), Precision, Recall, F1 Score, and segmentation area percentage. For clarity, the results for the U-Net model are listed first, followed by those for the Attention U-Net. This arrangement aims to provide a comprehensive overview of the performance of each model in segmenting Subarachnoid Hemorrhage (SAH) areas on brain CT scan images.

Table 1. Quantitative evaluation of U-Net model on selected samples.

Metric	Sample 1	Sample 2	Sample 3
Dice Score	0.57	0.57	0.73
IoU	0.39	0.40	0.57
Precision	0.50	0.79	0.81
Recall	0.65	0.45	0.66
F1 Score	0.57	0.57	0.73
Area %	3.35%	1.1%	2.76%

The U-Net model shows relatively consistent performance across the three samples, with the highest Dice Score of 0.73 achieved on the third sample and the largest predicted segmentation area (3.35%) observed in the first. The model also demonstrates strong recall across samples, indicating good sensitivity toward the target region, although some trade-offs with lower precision are noted.

Table 2. Quantitative evaluation of Attention U-Net model on selected samples.

Metric	Sample 1	Sample 2	Sample 3
Dice Score	0.57	0.57	0.73
IoU	0.39	0.40	0.57
Precision	0.50	0.79	0.81
Recall	0.65	0.45	0.66
F1 Score	0.57	0.57	0.73
Area %	3.35%	1.1%	2.76%

In contrast, the Attention U-Net model displays greater variability across the samples. In the first sample, it recorded a Dice Score of 0.61 and a Recall of 0.69, reflecting the model's capacity to detect dispersed SAH areas. However, in the second sample, performance dropped, with a Dice Score of 0.38 and IoU of 0.23. This suggests that spatial attention mechanisms, although effective, may not yet fully optimize performance for detecting very small or low-contrast structures.

3. 4 Aggregate Performance Comparison

Figure 8 presents representative slices from the test dataset used for aggregate evaluation. This visualization provides context on the diversity of SAH cases encountered, as well as the spatial complexity faced by the segmentation models.

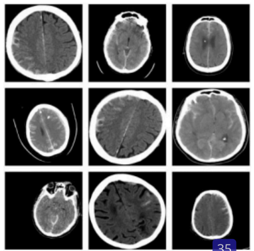

Figure 8. Representative brain CT scan slices from the test dataset

Subsequently, Table 3 presents the aggregate performance metrics of both models evaluated on the entire test set consisting of 86 batches. The evaluation utilizes five main metrics: Dice Score, IoU, Precision, Recall, and F1 Score. This table facilitates a direct comparison between U-Net and Attention U-Net in terms of global segmentation performance. U-Net demonstrates a higher precision (0.725), reflecting its tendency to avoid over-segmentation. On the other hand, Attention U-Net records higher scores in Dice (0.896), IoU (0.877), and Recall (0.557), indicating stronger sensitivity in capturing subarachnoid hemorrhage areas.

Table 3. Comparative evaluation metrics of U-Net and Attention U-Net on the full test set.

Metric	U-Net	Attention U-Net
Dice Score	0.867	0.896
IoU	0.848	0.877
Precision	0.725	0.637
Recall	0.478	0.557
F1 Score	0.507	0.553

Overall, this comparison reinforces that Attention U-Net is more suitable for scenarios requiring broad coverage and high sensitivity to small structures, whereas U-Net may be preferable when the clinical focus is on precision and background noise suppression. These findings support earlier sample-based analyses and provide justification for selecting models according to specific clinical or operational priorities.

Figure 9 displays a bar chart comparison of the aggregated evaluation metrics for U-Net and Attention U-Net. This visualization further substantiates the tabulated quantitative findings, clearly illustrating each model's relative strengths. Attention U-Net outperforms in Dice, IoU, and Recall, while U-Net leads in Precision. Such differences suggest model selection should align with segmentation objectives, whether for comprehensive detection or targeted precision.

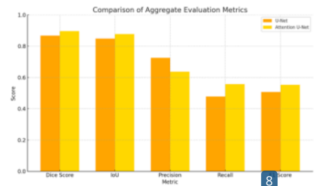

Figure 9. Visualization comparing evaluation metrics between U-Net and Attention U-Net.

3. 5 Analysis and Interpretation of Results

The findings obtained from both per-sample and full-dataset evaluations indicate that U-Net and Attention U-Net each exhibit distinct advantages in the task of Subarachnoid Hemorrhage (SAH) segmentation. On aggregate evaluation, the Attention U-Net model achieved a Dice Score of 0.896 and an IoU of 0.877, slightly outperforming the U-Net model which recorded a Dice Score of 0.867 and an IoU of 0.848. However, U-Net demonstrated higher precision (0.725 versus 0.637), indicating a tendency toward more conservative and less noisy predictions. Conversely, the higher recall of Attention U-Net (0.557 versus 0.478) reflects its stronger ability to identify SAH regions more comprehensively.

Visual inspection of segmentation outputs supports the quantitative findings. On samples with smaller and scattered SAH regions, Attention U-Net yielded more spatially accurate results, whereas U-Net performed better in detecting larger hemorrhagic areas, albeit sometimes including irrelevant regions. In general, both models demonstrated competent segmentation performance with complementary characteristics. Attention U-Net is more responsive to irregular and dispersed hemorrhages, while U-Net offers better local precision. These distinctions suggest that model selection should be aligned with the specific objectives of the target segmentation system.

4. CONCLUSION

Based on evaluations on the test dataset, Attention U-Net outperformed U-Net in terms of Dice Score and IoU, while U-Net achieved better precision with more conservative predictions. These results confirm that no single model consistently dominates across all metrics, but each offers specific strengths in different aspects of the segmentation task.

The findings demonstrate that deep learning-based segmentation approaches, particularly U-Net and Attention U-Net, hold strong potential for application in computer-assisted medical segmentation systems. This study also opens opportunities for future improvements through hybrid architectural exploration or transfer learning-based fine-tuning to enhance model robustness and generalization.

As future work, it is recommended to expand dataset size and diversity, consider alternative architectures such as Transformer-based segmentation models, and extend evaluations to multi-class segmentation tasks to enable broader validation across various types of intracranial hemorrhage.

5. REFERENCE

[1] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J Big Data*, vol. 6, no. 1, p. 60, Dec. 2019, doi: 10.1186/s40537-019-0197-0.

[2] N. M. Dubosh and J. A. Edlow, "Diagnosis and Initial Emergency Department Management of Subarachnoid Hemorrhage," *Emerg Med Clin North Am*, vol. 39, no. 1, pp. 87–99, Feb. 2021, doi: 10.1016/j.emc.2020.09.005.

[3] A. Arab *et al*., "A fast and fully-automated deep-learning approach for accurate hemorrhage segmentation and volume quantification in non-contrast whole-head CT," *Sci Rep*, vol. 10, no. 1, p. 19389, Nov. 2020, doi: 10.1038/s41598-020-76459-7.

[4] Y. Yu, M. Li, L. Liu, Y. Li, and J. Wang, "Clinical big data and deep learning: Applications, challenges, and future outlooks," *Big Data Mining and Analytics*, vol. 2, no. 4, pp. 288–305, Dec. 2019, doi: 10.26599/BDMA.2019.9020007.

[5] S. Umapathy, M. Murugappan, D. Bharathi, and M. Thakur, "Automated Computer-Aided Detection and Classification of Intracranial Hemorrhage Using Ensemble Deep Learning Techniques," *Diagnostics*, vol. 13, no. 18, p. 2987, Sep. 2023, doi: 10.3390/diagnostics13182987.

[6] M. D. Hssayeni, M. S. Croock, A. D. Salman, H. F. Al-khafaji, Z. A. Yahya, and B. Ghoraani, "Intracranial Hemorrhage Segmentation Using a Deep Convolutional Model," *Data (Basel)*, vol. 5, no. 1, p. 14, Feb. 2020, doi: 10.3390/data5010014.

[7] G. Litjens *et al*., "A survey on deep learning in medical image analysis," *Med Image Anal*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[8] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," May 2015.

[9] M. M. Khan *et al*., "A Deep Learning-Based Automatic Segmentation and 3D Visualization Technique for Intracranial Hemorrhage Detection Using Computed Tomography Images," *Diagnostics*, vol. 13, no. 15, p. 2537, Jul. 2023, doi: 10.3390/diagnostics13152537.

[10] L. Dai, Md Gapar Md Johar, and Mohammed Hazim Alkawaz, "Review of Semi-Supervised Medical Image Segmentation based on the U-Net," *Academic Journal of Science and Technology*, vol. 11, no. 1, pp. 147–154, May 2024, doi: 10.54097/gmhkht38.

[11] A. Vaswani *et al*., "Attention is All you Need," in *Advances in Neural Information Processing Systems*, I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds., Curran Associates, Inc., 2017. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

[12] O. Oktay *et al*., "Attention U-Net: Learning Where to Look for the Pancreas," Apr. 2018.

[13] F. El Abassi, A. Darouichi, and A. Ouaarab, "Comparative Analysis of U-Net with Transfer Learning and Attention Mechanism for Enhanced Medical Image Segmentation," 2024, pp. 551–560. doi: 10.1007/978-3-031-68653-5_52.

[14] X. L. Yang and Z. Y. Jin, "Att GGO-Net:A Semantic Segmentation Method of Lung CT Images with Self and Cross Attention Mechanism," *J Phys Conf Ser*, vol. 2504, no. 1, p. 012017, May 2023, doi: 10.1088/1742-6596/2504/1/012017.

[15] S. Tenny, J. Das, and W. Thorell, "Intracranial Hemorrhage - StatPearls - NCBI Bookshelf." Accessed: May 26, 2025. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK470242/

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