GAT_ASP-UNet: Unified Deep Learning Approaches — Ensemble-Based U-Net for Medical Image Segmentation

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Medical image segmentation demands precise boundary delineation even under dense-distribution and fuzzy-edge conditions. We present **GAT_ASP-UNet**, a novel encoder–decoder architecture that couples a Fixed-Volume Compressor (FSCM) with a Graph Attention (GAT) Bridge to introduce structured relational reasoning into skip connections at constant complexity $O(1024)$, independent of input resolution. Evaluated on four public benchmarks (CVC-ClinicDB, Kvasir-SEG, ISIC2018, and Breast Ultrasound-B), the model achieves a Dice score of 90.88% on dermoscopic data and demonstrates that GAT-enhanced skip connections improve boundary recall over standard baselines.

Additional Key Words and Phrases: medical image segmentation, U-Net, graph attention network, fixed-volume compression, ADFM, polyp detection

1 Introduction

Medical image segmentation is a critical prerequisite for objective clinical diagnosis, providing the spatial foundations for condition evaluation and surgical planning. Despite the dominance of U-shaped convolutional neural networks (CNNs), significant challenges persist in the precise delineation of "fuzzy edges" and the separation of objects within "dense distributions" [1, 2]. These difficulties arise from the inherent local inductive bias of standard convolutions, which often fail to capture long-range contextual dependencies, and the prohibitive computational costs of Vision Transformers (ViTs) when processing high-resolution medical volumes.

The motivation for this research is to enhance the "reusability of features" and "contextual reasoning" within a resource-constrained framework. Existing architectures such as MFA U-Net attempt multi-stage extraction, while DDS-UNet focuses on mitigating semantic gaps, yet neither fully addresses the need for structured relational reasoning across skip connections.

This paper introduces **GAT_ASP-UNet**, which leverages a novel integration of the Fixed Volume Compression module (FSCM) and a Graph Attention (GAT) Bridge. By constraining intermediate features to a fixed 32×32 volume, the model ensures that the complexity of relational reasoning is a constant factor $O(1024)$, independent of input resolution.

2 Related Works

The development of medical imaging architectures has focused on refining the encoder–decoder paradigm to bridge the gap between low-level spatial detail and high-level semantics.

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2.1 Standard U-Net

The baseline U-Net architecture utilises a symmetric contracting path to capture context and a symmetric expansive path to enable precise localisation via skip connections [1].

2.2 DDS-UNet

The Deep Dynamic Self-Adjusting U-Net (DDS-UNet) introduces the Lightweight Deformable Residual (LDR) module and a Semantic Mitigation Module (SMM). The LDR enhances the receptive field for contour extraction, while the SMM reduces the "semantic gap" between codec layers—discrepancies that inherently increase with network depth [2].

2.3 MFA U-Net

The Multi-Stage Feature Analysis Network (MFA U-Net) emphasises "multi-channel dimensional feature extraction" by reusing input images across parallel convolutional branches. Its primary extraction block processes inputs through channels of 8, 16, 32, and 64, fused into a 120-channel feature map before reduction back to 64 channels [3].

2.4 DoubleU-NetPlus

DoubleU-NetPlus extends the dual U-Net paradigm with a context-guided attention mechanism and multi-scale residual feature fusion. By coupling two U-Net branches with cross-attention, it captures both local boundary detail and global semantic context for robust semantic segmentation of medical images [4].

2.5 UCTransNet

UCTransNet replaces the standard skip connections in U-Net with a Channel-wise Cross-Fusion Transformer (CCT) module. This channel-wise perspective enables selective multi-scale feature fusion between encoder and decoder stages, substantially reducing the semantic gap inherent in deep skip connections [5].

3 Proposed Model

The GAT_ASP-UNet is engineered to provide multi-scale feature enrichment and relational context through a dual-path encoder and a triple-concatenation decoder. The overall architecture is illustrated in Figure 1 (see Appendix).

3.1 Advanced Feature Module (ADFM)

The ADFM is the primary engine for multi-scale context capture (Figure 2a). It employs parallel branches with 1×1, 3×3, 5×5, and dilated kernels alongside an ASPP block. Each branch incorporates a "downsampled self-attention" mechanism that operates on a reduced grid to manage computational overhead. Concatenated branch outputs are passed through a global multi-head attention (MHA) layer before final 1×1 fusion, with a residual connection preserving input information.

3.2 Fixed Volume Compressor (FSCM)

To ensure computational stability, the FSCM forces features into a compact 32×32 spatial volume using 1×1 channel reduction followed by adaptive average pooling. This bounds the complexity of subsequent attention and GAT layers to a constant factor $O(1024)$, making the most intensive parts of the network resolution-independent. The FSCM pipeline is shown in Figure 3 (see Appendix).

3.3 Graph Attention (GAT) Bridge

The GAT Bridge converts spatial features into a grid graph to perform relational reasoning (Figure 2b). Features are reduced to a target channel dimension C_r and pooled to a $P \times P$ grid. A 4-neighbourhood grid graph is constructed and a PyG `GATConv` layer is applied over the nodes. Following graph processing, features are upsampled and restored via a 1×1 convolution to match the skip connection dimensions.

3.4 GhostRFBCoordBottleneck

This lightweight bottleneck (Figure 4) utilises *GhostModules* for cheap feature expansion, a *LiteRFB* module (multi-branch dilated depthwise convolutions) to expand the receptive field, and *CoordinateAttention* to refine features through spatial-aware channel gating (Figure 4, Appendix).

3.5 Architectural Rationale

The dual-path encoder at each stage uses:

- **Path A:** encoder output → FSCM → ADFM → channel adapt → upsample to fuse.
- **Path B:** encoder output → MaxPool/downsample.

Both paths are concatenated and fused via a 1×1 convolution. In the decoder, a "triple-concat" strategy merges:

(1) direct encoder features,
(2) GAT bridge outputs, and
(3) previous decoder features re-processed via FSCM–ADFM.

4 Experiments and Results

4.1 Experimental Setup

- **Dataset split:** 80% training, 20% validation.
- **Training:** 100 epochs, learning rate $\eta = 10^{-4}$, Adam optimiser.
- **Loss Functions:** Dice + BCE (primary); Focal Tversky + IoU (secondary).
- **Augmentation:** 9 techniques including elastic transform, colour jitter, and random occlusion.
- **Metrics:** IoU, Dice, Precision, Recall, Accuracy.

4.2 Datasets

Table 1. Datasets used for evaluation.

Dataset	Modality / Target	Images
CVC-ClinicDB	Endoscopic / Polyp detection	612
ISIC2018	Dermoscopic / Skin lesions	2,596
Kvasir-SEG	Endoscopic / Polyp images	1,000
Breast Ultrasound B	Ultrasound / Breast lesions	163

4.3 Performance on External Datasets

The model generalises exceptionally well to dermoscopic images (ISIC2018 Dice: 90.88%). The lower IoU/Dice on Breast Ultrasound B suggests a need for domain-specific augmentation to handle ultrasound noise profiles. Figure 5 shows qualitative predictions across datasets.

Table 2. Results on external datasets (all values in %).

Dataset	Split	IoU	Dice	Prec	Rec	Acc
Kvasir-SEG	Val	76.17	86.14	88.99	84.27	95.86
	Train	74.48	85.03	88.07	83.13	95.60
ISIC2018	Val	83.61	90.88	93.64	88.81	96.24
	Train	82.62	90.28	92.37	88.88	96.04
Breast US B	Val	66.64	79.40	82.75	76.88	98.17
	Train	63.54	77.37	73.91	83.34	97.86

4.4 Comparative Analysis on CVC-ClinicDB

Table 3. Comparative analysis on CVC-ClinicDB (metrics in %).

Model / Variant	Val Loss	Val IoU	Val Dice	Val Acc	Val Prec	Val Rec
DDSUNet – Dice loss	0.11762	86.74	92.63	98.61	94.69	91.33
DDSUNet – Dice + BCE	0.04925	85.28	91.77	98.51	93.77	90.53
DDSUNet + GATConv	0.12696	86.39	92.47	98.60	93.77	91.91
Proposed – Focal Tversky	0.21342	72.58	83.22	96.76	83.59	84.99
Proposed – Dice + BCE	0.23182	76.30	86.14	97.54	88.98	84.58

While the proposed model demonstrates strong training metrics (Train Dice ≈90.9% on CVC), its validation performance lags behind the DDSUNet baselines, indicating overfitting or domain mismatch. Notably, the GATConv baseline variant achieved the highest validation recall (91.91%), empirically supporting the thesis that graph-based relational reasoning captures complex non-local boundaries.

5 Future Works and Conclusion

To mitigate the observed overfitting and improve generalisation, future work should prioritise:

- **Enhanced Regularisation:** Dropout and weight decay within ADFM and GAT Bridge for robustness to domain shifts.
- **Structural Ablations:** Investigation of GAT layer depth and attention head counts to optimise the balance between relational reasoning and parameter count.
- **Data Augmentation:** Stronger elastic transforms and random occlusion to better simulate variability in clinical endoscopic imaging.

In conclusion, GAT_ASP-UNet provides a sophisticated framework for integrating relational reasoning into medical segmentation. While it shows particular strength in dermoscopic analysis, further tuning is required to match state-of-the-art performance on endoscopic datasets.

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A Architecture Diagrams and Results

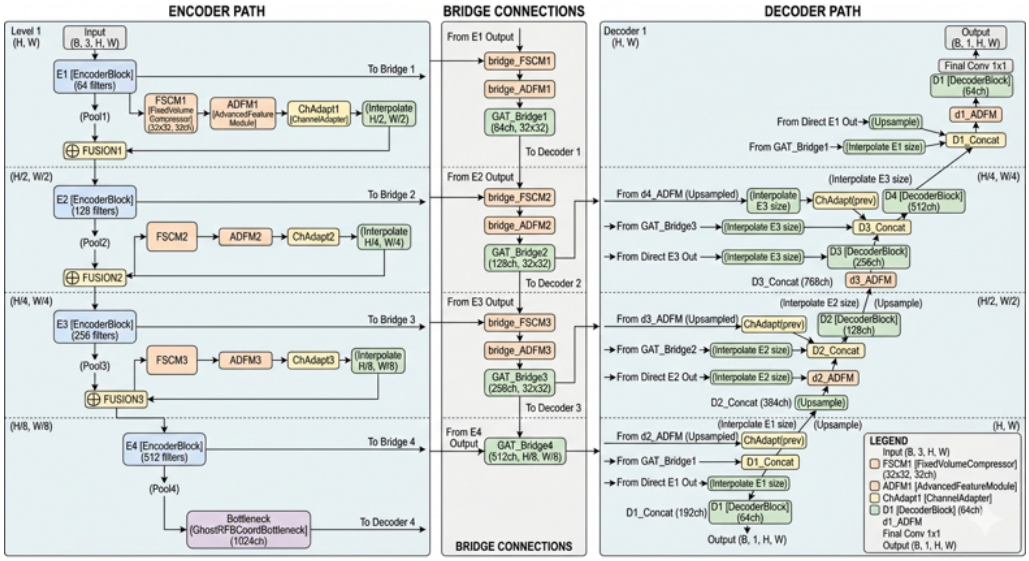
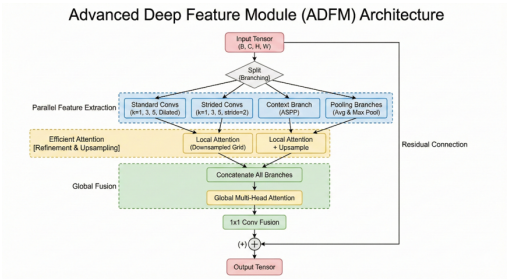
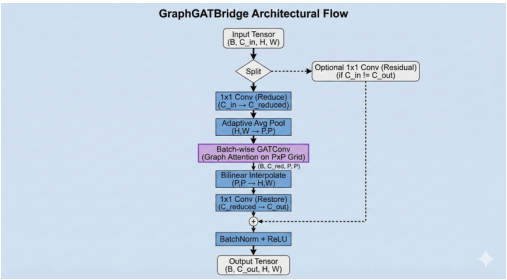


Fig. 1. Overall architecture of GAT_ASP-UNet. The dual-path encoder (Path A: FSCM→ADFM; Path B: MaxPool) feeds enriched features to the GAT Bridge skip connections. The triple-concat decoder (direct encoder | GAT skip | re-processed prev. decoder) reconstructs the segmentation mask.



(a) ADFM module.



(b) GAT Bridge module.

Fig. 2. Key sub-modules. (a) ADFM: 10 parallel branches with per-branch downsampled self-attention followed by global MHA. (b) GAT Bridge: pools to a $P \times P$ grid graph and applies GATConv before restoring spatial resolution.

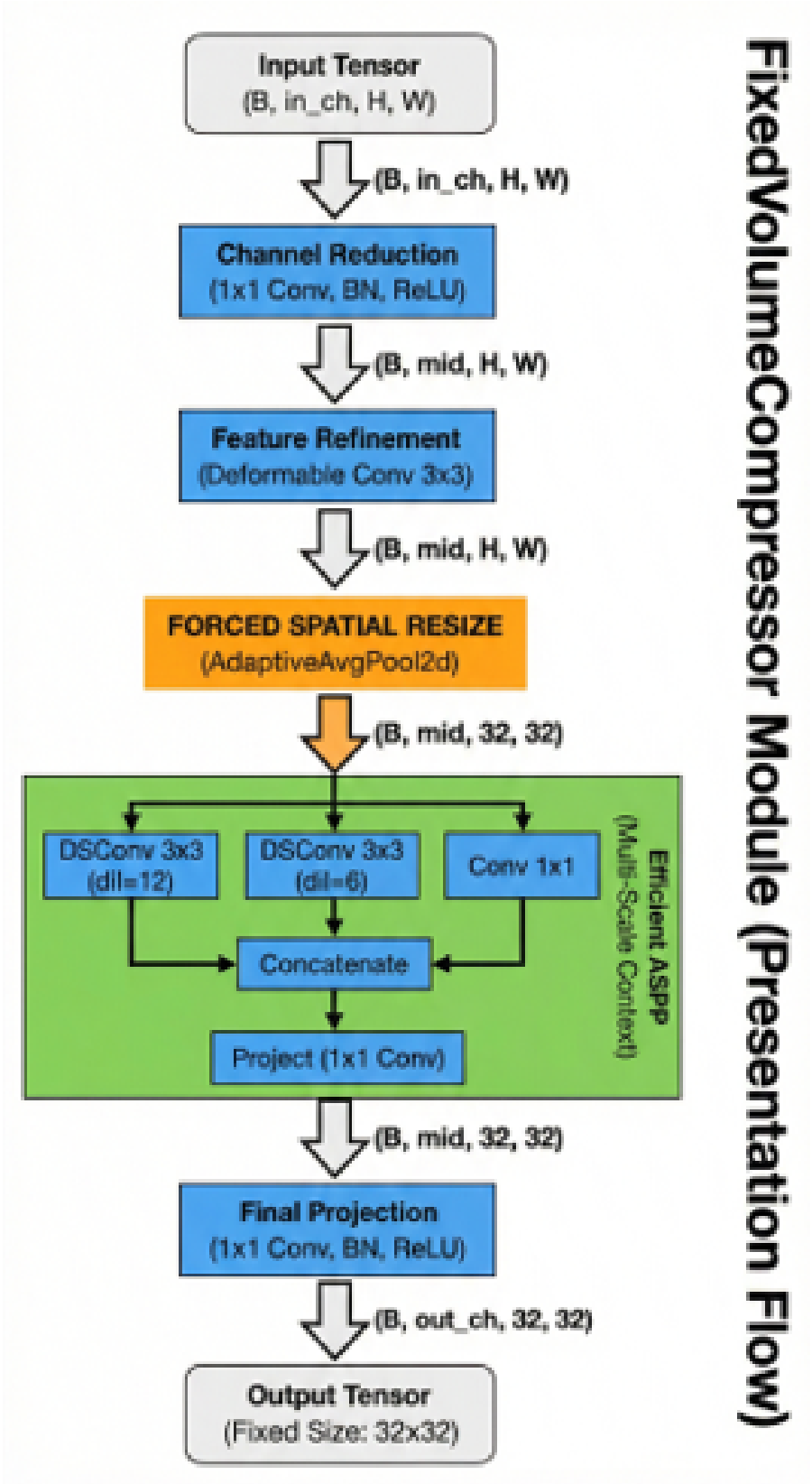


Fig. 3. Fixed Volume Compressor (FSCM): 1×1 channel reduction → deformable conv → AdaptiveAvgPool to

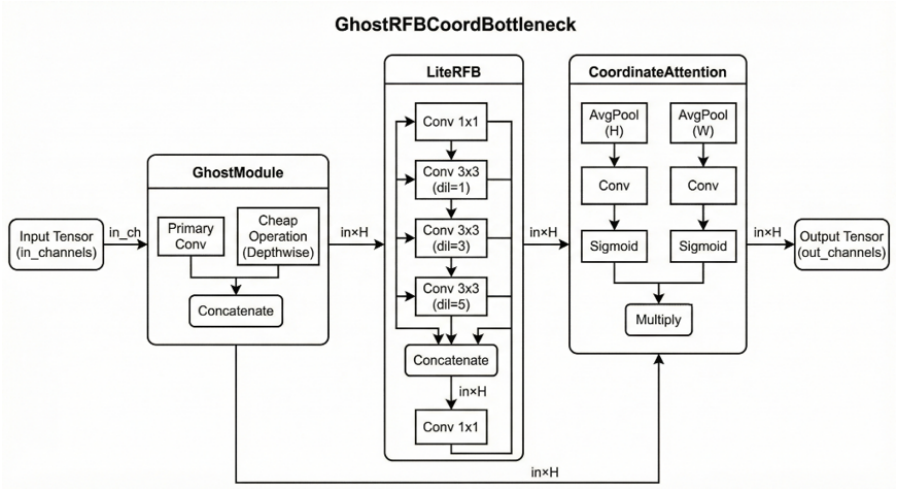


Fig. 4. GhostRFBCoordBottleneck: GhostModule expansion → LiteRFB multi-dilated depthwise branches → CoordinateAttention channel-spatial gating.

Fig. 5. Qualitative segmentation results on CVC-ClinicDB from the final GAT_ASP-UNet model. Each row shows the original endoscopic image, the ground-truth mask, and the predicted mask.

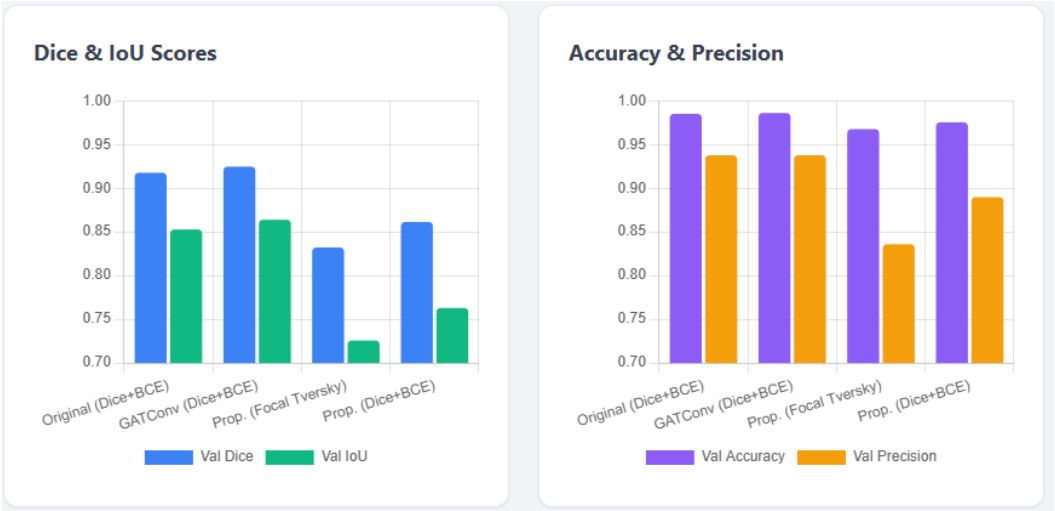


Fig. 6. Comparative results across baseline models and the proposed GAT_ASP-UNet. Columns represent different architectures; rows correspond to evaluation metrics on CVC-ClinicDB.