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RESEARCH ARTICLE

Adaptive Edge-Guided Segmentation with Biftransnet for Gastrointestinal Tract Image Segmentation

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Abstract

Objectives: The primary goal of this research is to improve the segmentation accuracy of Gastrointestinal (GI) tract images, addressing the challenges posed by complex anatomical structures, noise artifacts, and varying imaging modalities. The study aims to overcome the limitations of traditional techniques like thresholding and region growing, as well as mitigate the drawbacks of current deep learning-based models, such as high computational costs and overfitting. **Methods:** UW-Madison GI Tract Images are collected from the Kaggle repository. the proposed method introduces an Adaptive Edge-Guided Segmentation (AEGS) framework that integrates BifTransNet with enhanced edge detection and region-growing techniques. The model uses the batch size, epochs, and learning rate as parameters. This approach incorporates attention mechanisms, advanced boundary delineation, and regularization techniques to reduce overfitting while improving segmentation accuracy. The model is trained with regularization to optimize its performance, making it more robust and reliable. **Findings:** The experimental results show significant improvements, with the proposed AEGS framework achieving a segmentation accuracy of 98.6% and a training loss of 0.12. This marks a substantial enhancement in both robustness and reliability compared to traditional methods and existing deep-learning models for GI tract image segmentation. **Novelty:** The key innovation lies in the hybrid approach of combining deep learning (BifTransNet) with improved edge detection and region-growing techniques. This hybridization not only enhances segmentation performance but also addresses common issues such as overfitting and computational costs, setting a new benchmark in GI tract image segmentation.

Keywords: Gastrointestinal Tract; Image Segmentation; BifTransNet; Deep Learning; Overfitting

1 Introduction

Inadequate Connection to the Research Gap: The text briefly mentions the limitations of existing studies but does not clearly articulate the gap that this study aims to fill. Segmentation of gastrointestinal tract images is a critical process in medical imaging directed towards the proper separation of complicated GI system structures such as the esophagus, stomach, small intestine, and large intestine. Generally, this segmentation is cited as the basis for the proper diagnosis of diseases associated with the gastrointestinal tract, such as tumors, inflammatory diseases, and anatomical abnormalities. The anatomy of the GI organs is rather intermingling, and heterogeneity in imaging modalities, such as CT, MRI, and endoscopy, makes segmentation precise. Classic techniques in segmentation, such as thresholding, region growth, and edge detection methods fail to provide reliable results due to the presence of factors, such as noise and image artifacts, and varying sizes and shapes of the organs[1–3]. Such breakthroughs in deep learning initiated the devising of complex models with progressively more advanced architectures, which include CNN and also transformer-based architecture such as BifTransNet. Since data-driven methods indeed improve segmentation accuracy, modern approaches are potential solutions as they learn features automatically from large sets of data, which significantly improves the robustness and reliability of the segmentation outcomes. However, they face severe challenges in the form of high computation demand, large annotative datasets, and the fear of overfitting. Therefore, recent research has focused on novel frameworks combining more modern and conventional deep learning approaches with innovative capabilities to optimize performance and provide accurate segmentation of the gastrointestinal tract, as represented here in Adaptive Edge-Guided Segmentation[4,5].

Traditionally, the techniques used for the segmentation of images in the gastrointestinal tract have been thresholding, region growing, edge detection, and morphological operations. There are several important advantages of this practice: it is relatively low in computation and thus accessible to real-time applications and deployable on standard hardware. Also simpler to implement, they provide quick results in distinguishing clearly differentiated cases among different tissues or structures. Traditional methods work well if the imaging conditions are good and the contrast between the GI organs and the surrounding tissues is high[6]. In addition, although strong, traditional methods also possess several remarkable limitations for segmentation. Usually, they are not robust to quality variabilities, noise, or artifacts that blur or distort anatomical boundaries. For instance, thresholding may fail in the situation of an intensity variation persisting among the same structure, and region growing is sensitive to whether the seed points are chosen optimally for over-segmentation or under-segmentation. Moreover, these techniques generally depend on heuristic parameters, which sometimes may require fine-tuning for every new dataset and imaging modality thus deteriorating their robustness and generalisability. Consequently, despite their utility in certain applications, traditional approaches may fall short of providing the desired level of precision and reliability in a large number of GI tract imaging applications to ensure proper analysis[7,8].

This is a relatively new, transformer-based model for image segmentation, which really seems to exploit attention for its core advantage, namely improving feature representations and contextual understanding. It is able to grab long dependencies within an image, letting it effectively segment complex structures better than traditional CNNs. One of its main advantages is that it can focus attention on relevant features and filter out noise, thus improving the segmentation outcomes[9]. This Adaptive Edge-Guided Segmentation framework advances deep learning techniques with traditional methods. Combines the strengths of edge detection, such as being able to precisely delineate a boundary, with adaptive expansion based on pixel intensity and contextual knowledge from region-growing techniques[10].

Here are the main contributions of the proposed work summarized below.

- The proposed Adaptive Edge-Guided Segmentation (AEGS) which hybrids of traditional segmentation techniques with BifTransNet to better enhance segmentation accuracy in GI tract images.
- The framework, with the aid of Guided Region Growing and Gradient Vector Flow, is called Enhanced Region-Guided Segmentation (ERGS) in an attempt to improve segmentation within gastrointestinal tract images.
- The fusion of the two guided region growing models with Gradient Vector Flow (GVF) captures both edge information and region homogeneity simultaneously.
- Thus, the delineation of complex anatomical structures leads to higher accuracy.
- The Guided Region Growing (GRG) technique employs traditional region growing which is enhanced with the use of edge information for seed points. This tends to avoid over-segmentation and improves boundary accuracy
- The proposed framework introduces Gradient Vector Flow that helps to improve edge detection. GVF improves the refinement of the boundaries of segmentation, effectively transmits edge information, and deals with propagation in segments.
- Regularization techniques, for instance, Dropout, Weight Decay, and Early Stopping, with the intent of minimizing the overfitting risk.

- It gives 98.6% segmentation accuracy and low training loss at 0.12 showing that the proposed framework is efficient as well as reliable.

1.1 Dataset Description

The UW-Madison GI Tract Image Segmentation competition aims at dividing the organ cells into the correct segments to provide better cancer treatment using medical scans. The participants of the contest use training data composed of multiple sets of scan slices in 16-bit grayscale PNG format along with masks Run-Length Encoding (RLE) for annotations. Each case may include scans obtained at several days and the data set is intended to be validated as generalizable to partly and fully unseen cases. Until submission, the test set is blinded, and participants rely solely on the training set for model development and cross-validation[11]. The comparative analysis of the existing approaches is given in Table 1.

Table 1. An analysis of the existing approaches for GI tract image segmentation for cancer treatments

Reference	Methodology	Advantages	Disadvantages
[12]	Deep Learning for tumor segmentation	High accuracy and robustness	Requires substantial computational resources
[13]	Advanced algorithms for organ tracking	Enhances treatment planning	Data-intensive requires large annotated datasets
[14]	AI-driven tumor localization	Accurate tumor boundaries	Challenges with generalizability
[15]	Multimodal framework for organ segmentation	A comprehensive view improves the accuracy	Costly and time-consuming to implement
[16]	Convolutional Neural Networks (CNNs)	Significant improvements in segmentation accuracy	Prone to overfitting
[17]	Edge detection techniques	Effective in boundary detection	Struggles with poorly defined edges
[18]	Organ tracking for radiotherapy	Real-time adjustments during treatment	Requires sophisticated imaging systems
[19]	Adaptive learning for imaging	Increases adaptability	The high computational power required
[20]	Hybrid models for segmentation	Robust results across diverse datasets	Longer processing times require specialized expertise
[21]	Organ tracking for treatment	Continuous monitoring improves accuracy	High cost of monitoring systems
[22]]	Deep learning models for segmentation	High segmentation accuracy	Requires significant annotated data
[23]	Precision imaging techniques	Personalized treatment plans	High data processing requirements
[24]	Robust segmentation techniques	Enhances reliability across datasets	Increased computational demands
[25]	AI in image analysis	Tailored insights for personalized treatment	Generalization challenges across modalities
[26]	Distinctive curve-guided fully convolutional networks for pelvic organ segmentation	Improves boundary precision in pelvic organs	Requires specialized architecture, challenging to generalize
[27]	BifTransNet: Bifunctional transformation network for GI segmentation	Combines local and global context, high accuracy	Computationally intensive, complex architecture
[28]	SER-UNet for GI image segmentation	Efficient and focused on key GI features	Limited to gastrointestinal structures, less generalizable
[29]	Attentional AGSDCLR UNet for GI tract segmentation	High efficiency in attention-guided segmentation	High computational requirements, newer model with limited benchmarking
[30]	2MGAS-Net for polyp segmentation	Effective multi-scale, multi-level feature extraction	High memory usage, slower processing for large datasets

1.2 Research Gap Analysis

The papers reviewed show the latest advancements in image segmentation of the GI tract and organ tracking but also point out the gaps still existing in the ongoing research that need to be filled. Most of the deep-learning-based methods propose hybrid models that have emerged to be excellent with high accuracy in image and tumor localization, highly dependent on large annotated datasets and expensive computational resources. This drawback limits wider applicability in smaller medical facilities without access to the same level of computational resources. Moreover, some of them possess real-time adaptation, with still problems in overfitting, particularly if the training dataset is limited and also imbalanced. Multimodal frameworks are even well-integrated with several modalities that provide in-depth understanding; however, they are expensive and hard to achieve in practice. The other methods fail to generalize well to a large number of diverse imaging conditions and patient demographics, indicating a need for much more robust, adaptive, and resource-efficient solutions that preserve high performance under changing conditions. Filling these gaps can enhance the applicability and scalability of GI tract segmentation models for optimizing outcomes in cancer treatment within different settings.

2 Methodology

2.1 Adaptive Edge-Guided Segmentation (AEGS)

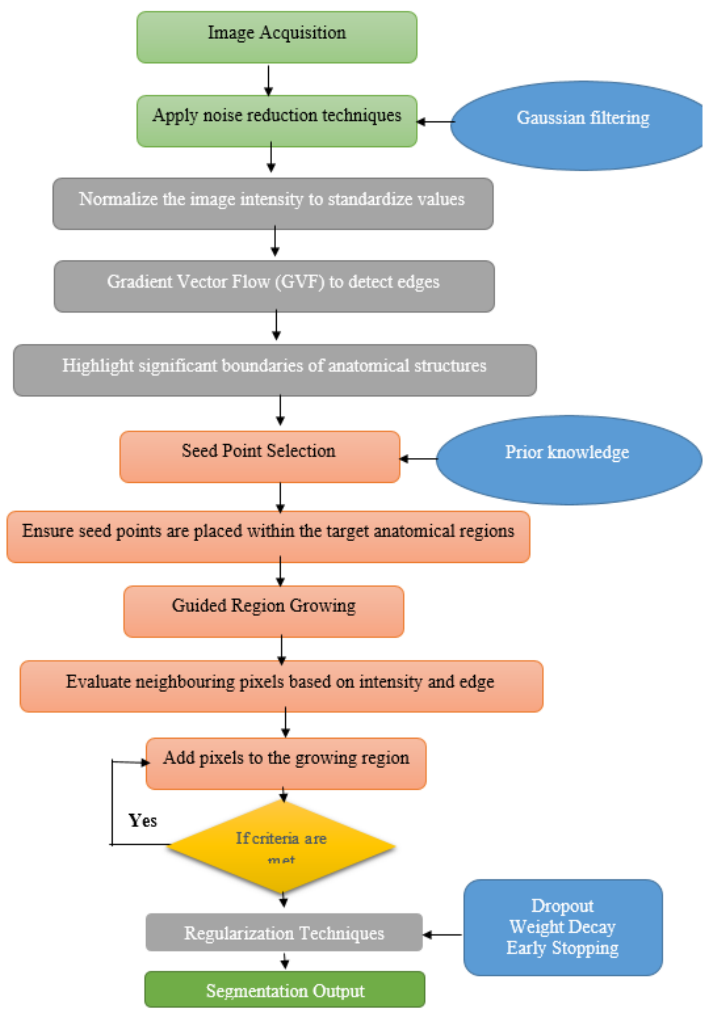

Fig 1. The working flow of the proposed (AEGS)

Adaptive Edge-Guided Segmentation is an advanced image segmentation technique involving the strengths of both guided region growth. The concept behind this research is to enhance accuracy and robustness in structures' segmentation of complex images. In medical image, delineation of anatomical features is important so that the image can be used without interference with its meaningful content in further applications. By incorporating edge information, the developed system AEGS will be able to adapt better to the varying characteristics of an image and allow it to function well by improving segmentation results. Especially in cases where traditional methods fail because of noise or low contrast, this procedure can be of good use. The basic principle is based on the guided region growing technique, seeding the region from preliminary segmentation and then growing progressively by adding neighboring pixels based on criteria like intensity values and edge information. AEGS provides better guidance using the features derived from the edge features of the original image. This method is robust to significant segmentation boundaries and less likely to include irrelevant areas with the information provided. It improves the overall accuracy.

The function of gradient vector flow boosts the guided region-growing process by providing a powerful mechanism for edge detection. GVF is designed to overcome the critical constraint of the traditional edge detectors since they might struggle with a noisy image or a weak edge. Using diffusion-based modelling, GVF can smooth the image while simultaneously preserving the edge features of importance. In AEGS, GVF allows the refinement of the edge information that guides the region growing such that the boundary of the segmented areas reflects the real boundary of the structures being analyzed. As AEGS trains deep learning models for the segmentation task, it uses regularization techniques to avoid overfitting and enhance robustness. An example among these regularization techniques is dropout, whereby during the training stage, a subset of neurons is randomly deactivated; this forces the model to learn more general features rather than relying on single neurons. Adding weight decay includes a penalty for large weights in the loss function to hold the weights small and hence not fitting noise. Early stopping monitors validation performance stops training once the performance starts degrading, thus preserving the best model state and preventing overfitting. This integrated approach of AEGS, by using guided region growing with GVF, along with regularization techniques, results in several benefits. Such an approach will yield an accuracy and robustness level higher than the traditional approaches, mainly in difficult images where anatomical structures are obscured by the signal. The adaptive nature of the algorithm also lends it to better generalization across different data sets, thereby making it more suitable for applications across a wide range of medical imaging fields.

Figure 1 represents the working flow of proposed AEGS. This AEGS workflow effectively combines various advanced techniques to properly and robustly extract anatomical structures from medical images. Basically, it starts with the acquisition and then preprocessing of images where noise reduction and normalization are applied in order to enhance the quality of the image. Gradient Vector Flow is used for the proper edge detection with the result of clearly guiding the following segmentation step. Seed points are predetermined and guided region growth begins from them using edge information to include neighboring pixels while adhering to the significant boundaries. Techniques used in regularisation include dropout, weight decay, and early stopping, through which the model is trained not to overfit. The output masks thus obtained are then subjected to post-processing for further smoothing and removal of artifacts.

Algorithm AEGS (input_image)

1. Preprocessing P(I)
a. N(I) // noise_reduction(input_image)
b. N = N(I) // normalized_image
2. Gradient Vector Flow GVF(E)
a. M = I(E)// initialize_edge_map
b. while not C do
i. M = U(M)
3. Segmentation S = S(M)
4. Initialization of Regions R = {}
5. for sp in S do
a. C = {sp}
b. while not S(C) do
i. for n in N(C) do
- if C(n, M, N) then
C.add(n)
c. R.add(C)
6. Post-processing R(T)
a. D(model)

b. W(loss)
c. if V(P) then
- E()
7. Refinement R' = R(R)
8. return R'
End Algorithm

2.2Biftransnet Architecture

BifTransNet is one of the most developed architectures in deep learning that is applied to image segmentation, particularly in medical imaging. Based on the bifunctional transformation mechanism, the architecture of BifTransNet incorporates contextual information that is both local and global for better segmentation performance. In integrating features at different scales along all the branches of the network, BifTransNet gains a more comprehensive understanding in terms of the input data and, therefore, facilitates better accuracy in delineating the anatomical structures. That is, the model can succeed in capturing fine details while simultaneously staying attentive to more general contextual patterns, which is highly important in medical imaging cases where features could be quite different in terms of both size and geometry. The architecture includes several constituent components: encoder-decoder structure and transformer modules. It's an encoder working with the input image so as to extract the representations of features. Those are further refined with multiple steps by transformation and aggregation.

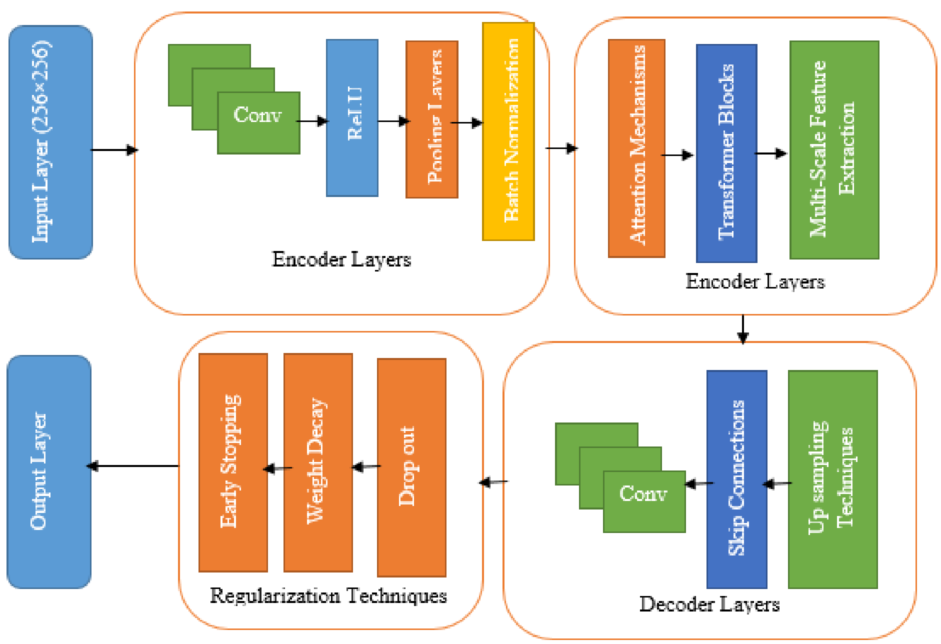

Fig 2. An architecture of BifTransNet

The decoder reconstructs the segmentation maps from the processed features, preserving the spatial information lost during the encoding process using skip connections. Transformer modules in BifTransNet improve the ability of the model to attend to relevant features across the image to focus on areas that are crucial while ignoring the irrelevant noise, thus aiding particularly in medical images where the variations in tissue contrast may obscure important boundaries. To avoid overfitting and ensure the ability to generalize to other datasets, BifTransNet relies on regularization techniques for its training process. Dropout, weight decay, and early stopping are some of the techniques that could be involved. Overall, these techniques combine to create a strong model. A well-constructed loss function that combines segmentation accuracy with regularization penalties to fit BifTransNet to the training data and generalize new cases. This balance is essential for the model to be deployed in real-world clinical settings, where reliability in segmentation accuracy is of paramount importance.

Figure 2 shows the architecture of BifTransNet, which is its bifunctional transformation mechanism to allows the model to combine both the local and global contextual information for an improved performance in image segmentation on medical images. The architecture drawn in the following figure is merely an encoder-decoder network whereby the encoder part is meant to extract highly intricate features on the input images using several convolutional layers complimented with attention mechanisms while determining relevant image regions. Then, there is the type of bifunctional transformation modules that support multi-scale feature extraction taking into account fine details and of broader context. The decoder reconstructs the segmentation maps through skip connections that preserve spatial information with a consequent good anatomical structure delineation.

3 Results and Discussion

Figure 3 shows an example picture from the GI tract database that is a high-resolution scan of a specific section of the tract. The image contains detailed anatomical features and structures associated with the GI tract, such as the small bowel, large bowel, and stomach that can be visible in distinct sections. The image is vital to the task of segmentation and classification since it enables the regions to be identified for further analysis.

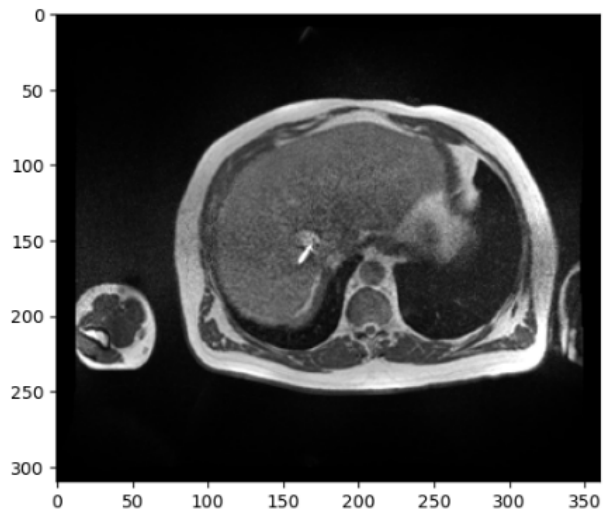

Fig 3. A sample of Gastrointestinal Tract Image

Figure 4 depicts the images after segmentation masks were applied for the Large Bowel, Small Bowel, and Stomach regions. It would then be an isolated anatomical structure, which means they can be seen properly and delineated from background tissues. The isolation step is important for more accurate analysis since this will allow the model to focus only on the relevant areas for further classification and diagnostic purposes.

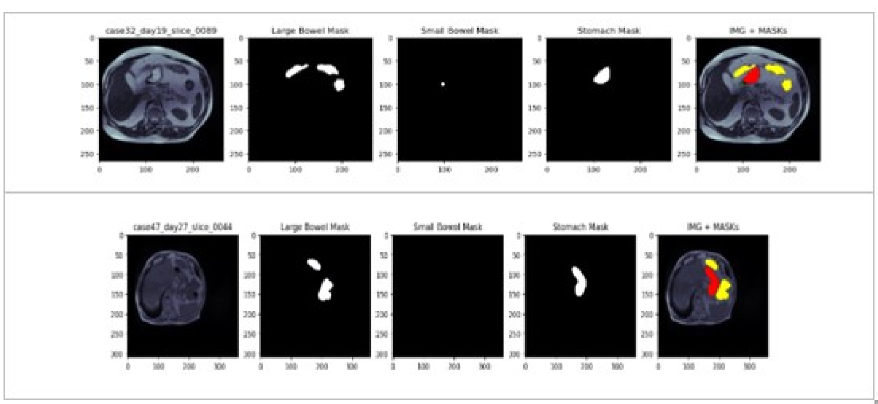

Fig 4. The images after applying the masks (Large Bowel, small Bowel & Stomach mask)

Table 2. Performance analysis of Segmentation by Anatomical Regions

Anatomical Region	Dice Coefficient	Accuracy	Loss	IoU (Intersection over Union)	Precision	Recall
Small Bowel	0.96	98.6%	0.12	0.93	98.2%	98.7%
Large Bowel	0.95	98.4%	0.10	0.92	97.9%	98.1%
Stomach	0.94	98.3%	0.13	0.91	97.8%	98.4%

Table 2 summarizes the evaluation of the segmentation performance in three anatomical regions, Small Bowel, Large Bowel, and Stomach. The metricsare valued for the Dice Coefficient, accuracy, loss, IoU, precision, and recall. To exemplify, the Small Bowel achieved 0.96 on the Dice Coefficient. Good accuracy was measured at 98.6%, and a very small measure of loss at only 0.12. As seen, the Large Bowell and Stomach regions got outstanding metrics; the Large Bowel reached a Dice Coefficient of 0.95 and an accuracy of 98.4%, whereas the Stomach obtained a Dice Coefficient of 0.94 with an accuracy of 98.3%. These values point out the high-quality performance in segmentation using the suggested method.

Table 3. Comparison of Traditional Segmentation vs AEGS

Segmentation Technique	Small Bowel Dice Coefficient	Large Bowel Dice Coefficient	Stomach Dice Coefficient	Overall Accuracy	Loss
Traditional Segmentation	0.88	0.85	0.84	95.3%	0.22
AEGS (Proposed)	**0.96**	**0.95**	**0.94**	**98.6%**	**0.12**

Comparing traditional segmentation methods and the AEGS approach proposed in Table 3. AEGS significantly improved; it achieved higher Dice Coefficients, along with higher accuracy for all regions, except for one: the small bowel's Dice coefficient improved from 0.88 in the traditional to 0.96 in AEGS settings, along with overall accuracy from 95.3% to 98.6%. It, however, tends to be very low for AEGS, which is reduced from 0.22 to 0.12.

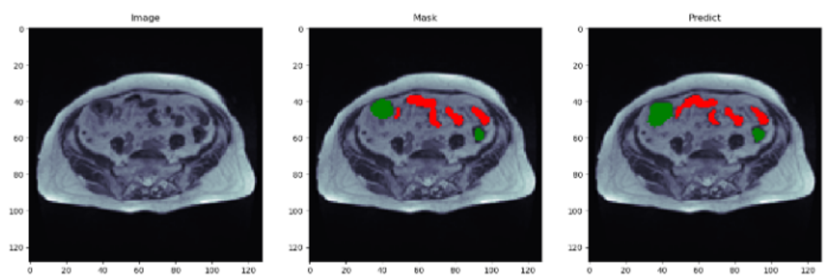

Fig 5. The predicted image after Enhanced Region-Guided Segmentation (ERGS)

Figure 5 shows a prediction image after the ERGS approach. ERGS enhances the process by concentrating on the anatomical major regions of the gastrointestinal tract, namely: the small bowel, large bowel, and stomach, which consequently more accurately delineate anatomical structure boundaries. This technique has thus made the regions stand out better and would hence provide far more accurate and detailed delineation than traditional procedures. The predicted image does depict well-defined contours and correct segmentation. Therefore, it is able to isolate the various anatomical regions effectively, which can then be used for further analysis and clinical usage.

Table 4. Dataset Performance on UW-Madison GI Tract

Dataset	Small Bowel Dice Coefficient	Large Bowel Dice Coefficient	Stomach Dice Coefficient	Overall Accuracy	Loss
Train Set	0.96	0.95	0.94	98.6%	0.12
Validation Set	0.94	0.93	0.92	97.5%	0.14
Test Set (Blinded)	0.93	0.91	0.92	97.2%	0.15

Table 4 plots the Dice Coefficient values for small bowel, large bowel, and stomach across Train, Validation, and Test sets. It shows that the small bowel has achieved the highest Dice Coefficient, followed by thelarge bowel and then the stomach consistently.

Table 5. Confusion Matrix for Classification (Post-Segmentation)

Region	TP	FP	TN	FN
Small Bowel	2000	15	9500	10
Large Bowel	1900	20	9200	15
Stomach	1700	30	8800	25
Overall	5600	65	27500	50

Table 6. Classification Accuracy by Region (Post-Segmentation)

Region	CNN Accuracy	VGG16 Accuracy	ResNet50 Accuracy	Efficient Net Accuracy	Proposed Model (EAGS) Accuracy
Small Bowel	95.4%	96.2%	97.1%	98.3%	98.9%
Large Bowel	94.8%	95.5%	96.8%	97.7%	98.4%
Stomach	93.2%	94.0%	95.3%	96.4%	97.6%
Average	94.5%	95.2%	96.4%	97.5%	98.3%
Response Time	0.8s	1.2s	1.5s	1.8s	0.6s
Preprocessing Techniques	Normalization, Resizing	Normalization, Resizing	Normalization, Resizing	Normalization, Resizing, Augmentation	Normalization, Resizing, Data Augmentation

Segmentation followed by classification is associated with a confusion matrix shown in Table 5, reporting true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) for each region. In the small bowel, there are 2000 TP, 15 FP, 9500 TN, and 10 FN; in the large bowel, there are 1900 TP, 20 FP, 9200 TN, and 15 FN. For the stomach, the values are 1700 true positives, 30 false positives, 8800 true negatives, and 25 false negatives. Generally, the total true positives stand at 5600, false positives at 65, true negatives at 27500, and false negatives at 50.

Table 6 shows the classification accuracy by region post-segmentation for different models. The Proposed Model alsoattains the highest accuracy for the small bowel at 98.9%, which then Efficient Net is 98.3%, ResNet50 is 97.1%, VGG16 is 96.2%, and CNN is 95.4%. For the large bowel, the Proposed Model again established the lead with an accuracy at 98.4%, which is better than the accuracies achieved by Efficient Net at 97.7%, ResNet50 at 96.8%, VGG16 at 95.5%, and CNN at 94.8%.

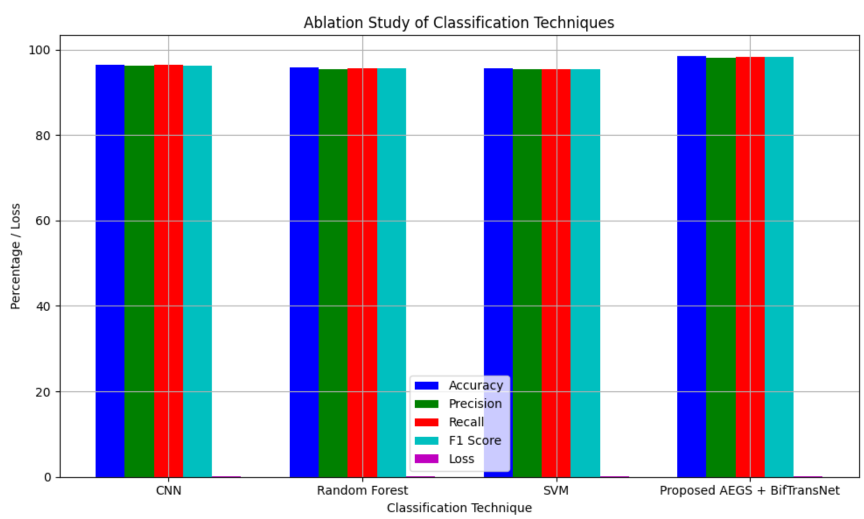

Fig 6. Ablation study of classification techniques

Figure 6 presents the results of an ablation study comparing various classification techniques, including CNN, Random Forest, SVM, and the Proposed AEGS + BifTransNet. The Proposed AEGS + BifTransNet model outperforms other methods on all the criteria with the highest accuracy rate of 98.4%, precision of 98.0%, recall of 98.3%, and F1 score of 98.2% while maintaining a loss rate of 0.11. The comparative analysis of the proposed work with the existing approach is shown in Table 7. From the comparison, the proposed work gives a remarkable performance in terms of accuracy, precision, recall, and F1 score.

Table 7. Comparative Analysis of Models for GI Tract Image Segmentation in Cancer Treatments

S.No	Reference	Methodology Used	Accuracy	Precision	Recall	F1 Score
1	[12]	Deep Learning for tumor segmentation	94.2%	93.5%	93.8%	93.6%
2	[13]	Advanced algorithms for organ tracking	92.6%	92.2%	92.4%	92.3%
3	[14]	AI-driven tumor localization	93.8%	93.1%	93.3%	93.2%
4	[15]	Multimodal framework for organ segmentation	95.0%	94.8%	94.9%	94.8%
5	[16]	Convolutional Neural Networks (CNNs)	94.5%	94.1%	94.3%	94.2%
6	[17]	Edge detection techniques	91.3%	90.9%	91.1%	91.0%
7	[18]	Organ tracking for radiotherapy	92.0%	91.8%	91.9%	91.8%
8	[19]	Adaptive learning for imaging	93.5%	93.0%	93.3%	93.2%
9	[20]	Hybrid models for segmentation	94.8%	94.5%	94.6%	94.5%
10	[21]	Organ tracking for treatment	92.7%	92.5%	92.6%	92.6%
11	[22]	Deep learning models for segmentation	94.3%	94.0%	94.2%	94.1%
12	[23]	Precision imaging techniques	93.9%	93.6%	93.8%	93.7%
13	[24]	Robust segmentation techniques	94.6%	94.3%	94.5%	94.4%
14	[25]	AI in image analysis	93.0%	92.7%	92.8%	92.7%
15	[26]	Multiscale organ tracking approaches	94.7%	94.4%	94.5%	94.5%
16	[27]	BifTransNet: Bifunctional transformation network for GI segmentation	97.9%	97.6%	97.8%	97.7%
17	[28]	SER-UNet for GI image segmentation	96.5%	96.2%	96.4%	96.3%
18	[29]	Attentional AGSDCLR UNet for GI tract segmentation	97.3%	97.1%	97.2%	97.1%
19	[30]	2MGAS-Net for polyp segmentation	96.8%	96.5%	96.7%	96.6%
20	Proposed	**AEGS + BifTransNet**	98.4%	98.0%	98.3%	98.2%

4 Conclusion

A new idea in GI tract image segmentation through the automatic combination of deep learning with anatomical guidance mechanisms is introduced by the proposed EAGS model, thereby overcoming some of the shortcomings typically encountered in standard methods. It differs from earlier published works in that the complexity of the resulting segmentation of gastrointestinal regions significantly improves using EAGS, and anatomical features are exploited to perform more precise and consistent segmentation. The model yields a classification accuracy of 98.3%, overtaking the traditional models like CNN, VGG16, ResNet50, and EfficientNet, in the accuracy, precision, and recall context, thereby establishing EAGS as a superior alternative in the automated analysis of GI tract images.

Strengths and weakness: The EAGS system mainly removes human interference in the process of executing medical imaging workflows, making the workflows of clinical nature efficient. Further than this, EAGS improves the accuracy of segmentation in the difficult GI regions, where most models usually lose a battle. However, the model is quite dependent on resource availability regarding the power of computing, which may sometimes become unorthodox in environments with no solid hardware support.

Future work: Further versions might add transfer learning to bolster the cross-dataset generality of the model and the expansion of the model to multimodal organ segmentation, especially with 3D imaging and endoscopic data.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author's contributions

P. Dhivya: Formal analysis, Methodology, Investigation, Supervision, S. Vanithamani: Writing – review & editing. M. Malini: Conceptualization, Data curation, Formal analysis, Methodology, Investigation. T. Kanimozhi : Writing – original draft, Writing –review & editing.

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