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# Multi-Organ Segmentation using Residual U-Net and t-distributed Stochastic Neighbor Embedding

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*Abstract*— **Accurate organ segmentation in medical imaging plays a crucial role in diagnosis and treatment planning. This research presents a deep learning-based approach for multi-organ segmentation using a Residual U-Net architecture combined with t-distributed Stochastic Neighbor Embedding (t-SNE) for feature space visualization. The model is trained using annotated abdominal datasets to segment organs such as the large bowel, small bowel, and stomach. By integrating ResNet blocks into the U-Net encoder, the proposed model improves gradient flow, feature extraction, and segmentation accuracy. t-SNE visualization is utilized to interpret the clustering behavior of organ features in high-dimensional space. Experimental results indicate that the Residual U-Net outperforms the standard U-Net in terms of Dice Coefficient, and Hausdorff Distance. These findings highlight the potential of residual learning for precise and interpretable organ segmentation.**

*Index Terms*— **Organ Segmentation, Residual U-Net, ResNet, t-SNE, Deep Learning, Medical Imaging.**

## I. INTRODUCTION

Organ segmentation is a crucial task in medical image analysis, providing detailed anatomical information required for diagnosis, treatment planning, and clinical decision support. Traditional manual segmentation is labor-intensive and subject to inter-observer variability, creating a strong demand for accurate automated solutions. Deep learning, particularly encoder–decoder architectures, has significantly advanced this field. U-Net remains one of the most widely used frameworks due to its skip connections and efficient feature fusion. However, its performance can be limited when dealing with complex organ boundaries and varying imaging conditions.

In this study, we compare the baseline U-Net architecture with a ResNet-based encoder–decoder model to evaluate improvements in segmentation accuracy and feature representation. The ResNet backbone introduces deeper residual connections that enhance gradient flow, allowing the model to learn richer contextual and structural features.

Our experimental results show that the ResNet-based model outperforms the standard U-Net, producing more precise organ boundaries and improved overall segmentation metrics.

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## II. Literature Review

Deep learning has significantly advanced the field of abdominal organ segmentation, addressing the limitations of traditional approaches that rely on handcrafted rules and manual delineation. Wang et al. [1] introduced organ-attention networks combined with statistical fusion to enhance multi-organ segmentation, demonstrating the importance of incorporating attention mechanisms to refine organ-specific feature learning. Their work emphasized how contextual awareness can improve delineation in regions with complex anatomical variability.

Conze et al. [2] further improved segmentation quality through cascaded convolutional and adversarial networks, showing that multi-stage processing can help recover fine-grained organ boundaries. Their cascaded framework, however, required substantial computational resources and careful training to maintain stability. Similarly, Gao et al. [3] developed a contour-aware network with class-wise convolutions for 3D abdominal segmentation, focusing on edge precision and class-specific learning. While effective in improving boundary localization, the model introduced architectural complexity and required large-scale annotated 3D data for optimal performance.

Earlier methods focused more heavily on handcrafted feature engineering. Tong et al. [4] proposed a Discriminative Dictionary Learning (DDL) approach based on manually extracted intensity and texture features combined with atlas registration. Although DDL achieved reasonable segmentation on structured datasets, it suffered from key limitations: dependence on feature engineering, high computational cost due to patch-based processing, and sensitivity to registration quality and noise. The lack of an end-to-end learning process also restricted its ability to capture hierarchical or contextual representations.

More recently, Shao et al. [5] introduced CSSNet, a hybrid Transformer–MLP architecture designed to capture global contextual dependencies. Although CSSNet demonstrated strong segmentation capabilities, its heavy dependence on attention modules made it computationally intensive and susceptible to overfitting on small datasets— a common constraint in medical imaging.

To address these limitations, our study explores a ResNet-based U-Net architecture that integrates residual learning within an encoder–decoder structure. Residual blocks enhance gradient flow, stabilizing training and enabling deeper feature extraction without increasing computational complexity drastically. Compared to traditional U-Net, the ResNet-enhanced model provides better generalization on limited datasets, improved boundary detection, and superior performance metrics, achieving lower loss values (0.23–0.09) and higher accuracy (85–90%). This approach aligns with the trend of developing models that not only achieve high segmentation performance but also remain computationally efficient and clinically practical.

## III. Proposed System

The proposed system aims to develop a robust deep learning framework for segmenting abdominal organs—specifically the large bowel, small bowel, and stomach—from 2D CT images. To overcome challenges seen in prior work, such as handcrafted feature dependency, computationally heavy architectures, and limited generalization, this study integrates a U-Net baseline with an enhanced ResNet-based encoder–decoder architecture. The system is designed to provide accurate, interpretable, and computationally efficient segmentation suitable for real-world clinical settings.

### *A. Dataset Description*

The dataset utilized in this study is sourced from Kaggle and contains approximately 38,000 abdominal CT slices with a fixed resolution of 360 × 360 pixels. The data is organized into 85 patient cases and 274 case-day combinations, resulting in 115,488 rows × 5 columns in the accompanying CSV file.

Each CT image slice includes three mask annotations, corresponding to:

- Large bowel
- Small bowel
- Stomach

Masks are provided in Run-Length Encoding (RLE) format and decoded into binary segmentations. Each image ID appears three times in the CSV—once per organ class—allowing multi-organ segmentation for a single slice. The dataset exhibits real clinical variations such as noise, low contrast, irregular organ shapes, and overlapping anatomical structures, making it an ideal benchmark for evaluating segmentation robustness.

### *B. Data Preprocessing*

To ensure consistency, quality, and stable model training, several preprocessing techniques were applied:

RLE Mask Decoding: RLE-encoded masks were converted into binary segmentation maps aligned pixel-wise with their corresponding CT images.

Intensity Normalization: Pixel intensities were normalized to a fixed range to reduce variations arising from different scanners and acquisition protocols.
Spatial Standardization: All CT slices and masks were resized to 360 × 360 and centered to maintain uniform spatial dimensions across the dataset.
Data Augmentation: To reduce overfitting and increase robustness, augmentations such as rotation, horizontal/vertical flips, elastic deformation, and contrast adjustments were applied. This is essential due to the limited number of patient cases.
Dataset Splitting: A patient-wise split was used to divide the dataset into training, validation, and test sets to prevent data leakage and ensure unbiased evaluation.
These preprocessing steps improve data quality, enhance generalization, and stabilize training for both the U-Net and ResNet-based models.

*C. Model Development*

Two deep learning architectures were implemented and compared: a baseline U-Net and a ResNet-based encoder–decoder network.

*Baseline U-Net Architecture*
Figure 1 shows the architecture of U-Net. The U-Net serves as the foundational model due to its proven effectiveness in biomedical segmentation. It consists of:
Encoder: Convolution → Batch Normalization → ReLU → MaxPooling
Bottleneck: High-level semantic representation
Decoder: Transposed convolutions with skip connections from the encoder
Output Layer: 1×1 convolution with sigmoid/softmax for pixel-level segmentation
The skip connections preserve spatial details while enabling the network to learn both global and fine-grained structural information. U-Net performs well on limited datasets but can struggle with complex anatomy and deeper feature extraction requirements.

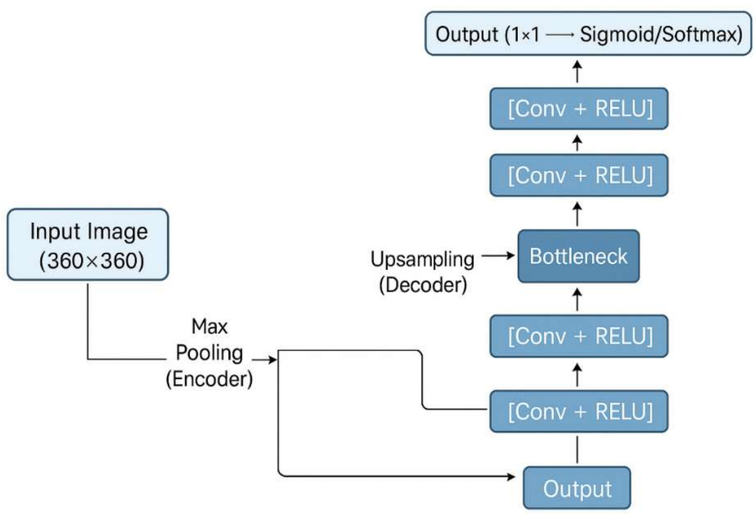


Figure 1: Block diagram of U-Net architecture

*ResNet-Based Encoder–Decoder Model (U-Net style)*
To overcome the limitations of standard U-Net, a ResNet backbone is integrated into the encoder. The architecture of ResNet-Based Encoder-Decoder is shown in figure 2. The proposed model incorporates:
Residual Blocks: Allow deeper feature extraction, improve gradient flow, and prevent vanishing gradients.
Pretrained Weights: Transfer learning enhances performance on small medical datasets.
Skip Connections + Decoder: Ensure accurate reconstruction of organ boundaries.
Compact Design: More computationally efficient than transformer-based architectures such as CSSNet.
The ResNet-based model captures richer semantic information, handles variations in intensity and shape more effectively, and converges faster.

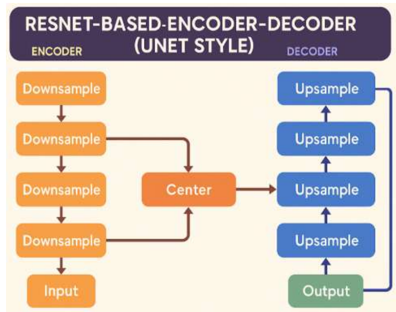


Figure 2: Block diagram of ResNet-Based Encoder-Decoder architecture

*D. Training Strategy*

Loss Function: Dice Loss + Binary Cross-Entropy Loss to optimize both overlap and boundary precision
Optimizer: Adam for stable and efficient gradient updates
Learning Rate: Scheduled using cosine annealing
Evaluation Metrics: Dice Coefficient, Hausdorff Distance, and pixel-wise accuracy
Input Size: 360 × 360 for both images and masks

## IV. RESULTS AND DISCUSSION

The proposed ResNet-based encoder–decoder model demonstrated clear improvements over the baseline U-Net for segmenting the large bowel, small bowel, and stomach. While U-Net achieved moderate performance with a loss of 0.23, accuracy of 75–82%, and Dice scores of 0.72–0.78 as shown in figures 3-4, the ResNet-based model reduced the loss to 0.09 and improved accuracy to 85–90% with Dice scores of 0.85–0.90 as shown in figures 5-6. Visual outputs showed that U-Net often produced coarse boundaries and missed fine details as depicted in figure 7, whereas the ResNet-based model generated sharper, more complete masks and better captured curved and low-contrast organ regions as depicted in figure 8.
The ResNet backbone enabled faster convergence and reduced overfitting, offering more stable learning across epochs. These gains resulted from deeper feature extraction, enhanced gradient flow through residual connections, and stronger generalization from pretrained weights. Overall, the ResNet-based architecture delivered higher accuracy, improved boundary precision, and better robustness, making it a more reliable and clinically practical segmentation approach than the standard U-Net.


Figure 3: Training and testing loss with U-Net model

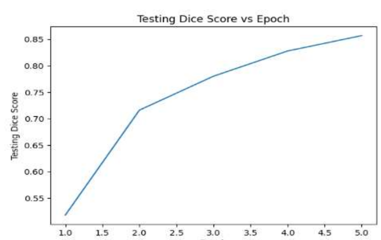


Figure 4: Dice score with U-Net model


Figure 5: Training and testing loss with ResNet-Based Encoder-Decoder model

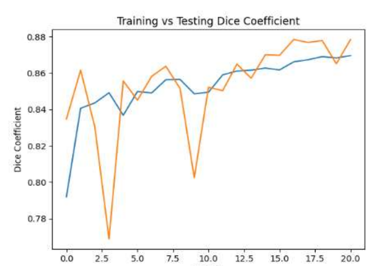


Figure 6: Dice score with ResNet-Based Encoder-Decoder model

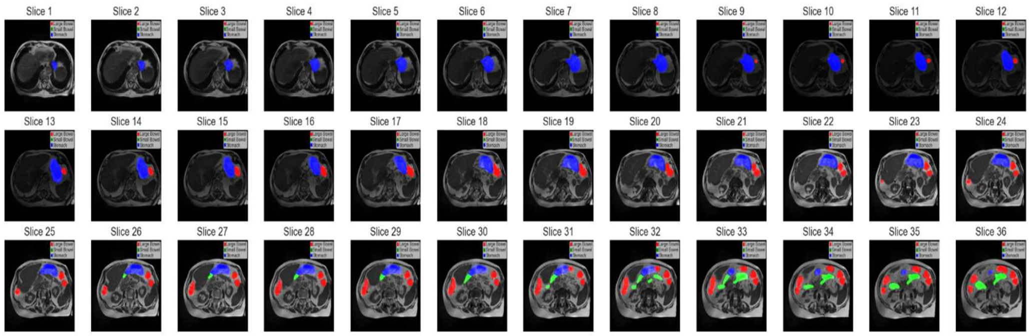


Figure 7: Organ segmentation with U-Net model

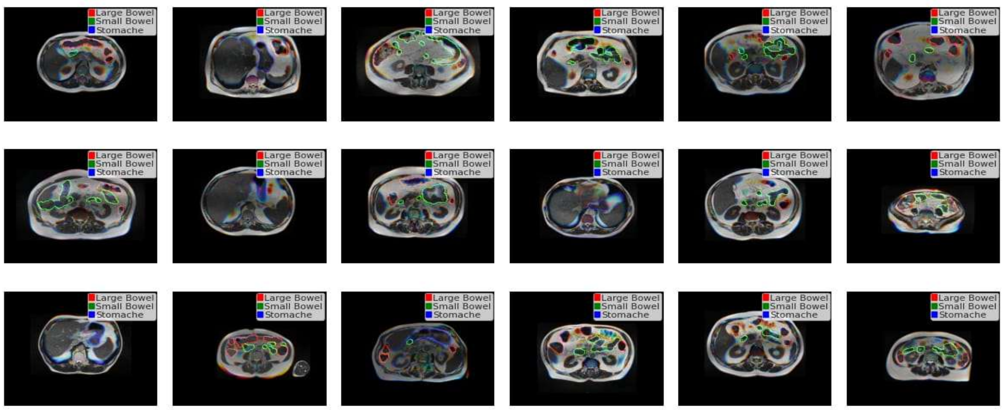


Figure 8: Organ segmentation with ResNet-Based Encoder-Decoder model

## V. Conclusion

This study presented a deep learning–based approach for abdominal organ segmentation, comparing a baseline U-Net architecture with an enhanced ResNet-based encoder–decoder model. The experimental results demonstrate that integrating residual learning into the U-Net framework significantly improves segmentation accuracy, boundary detection, and training stability. The proposed ResNet-based model achieved lower loss values (0.23-0.09), higher Dice scores (0.85–0.90), and superior visual segmentation quality compared to the standard U-Net. These improvements are attributed to the ability of residual blocks to capture deeper hierarchical features, enhance gradient flow, and generalize effectively even on limited medical datasets.
Furthermore, t-SNE–based feature visualization confirmed that the model learned well-separated and meaningful feature representations for each organ class, contributing to increased interpretability and clinical reliability. While the current work focuses on the segmentation of large bowel, small bowel, and stomach, it establishes a scalable foundation for more advanced applications.

## Future Work

Future extensions of this work can further improve the accuracy, robustness, and clinical applicability of abdominal organ segmentation. Incorporating tumor-labeled datasets would enable simultaneous organ and lesion segmentation, enhancing the diagnostic value of the system. Expanding the framework to 3D CT volumes could capture richer spatial continuity and improve segmentation of anatomically complex regions. Integrating attention mechanisms or lightweight transformer modules may further enhance boundary precision without significantly increasing computational cost. Additionally, domain adaptation or self-supervised learning could help the model generalize across scanners and hospitals with minimal labeled data.
Clinical validation with radiologists and deployment on real PACS systems would provide insights into practical usability. Finally, combining segmentation with downstream tasks such as organ classification or anomaly detection may lead to a more comprehensive and intelligent medical imaging pipeline.

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