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Optimization of Deep Learning Models for Automated Medical Image Segmentation in Multi-Center Diagnostic Systems

Dr. Olivia Bennett[1], Dr. Marco Conti[2]
[1]Department of Biomedical Engineering, University of Glasgow, Glasgow, United Kingdom
[2]Department of Information Engineering, University of Bologna, Bologna, Italy
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Abstract

Accurate image segmentation is a critical prerequisite for computer-assisted diagnosis and treatment planning. This study investigates the optimization of deep learning architectures for automated segmentation of medical images obtained from multiple healthcare institutions. Several convolutional neural network and transformer-based models were evaluated using standardized datasets containing magnetic resonance imaging and computed tomography scans. The proposed optimization strategy combined adaptive learning schedules, data augmentation techniques, and cross-institutional validation procedures to improve model robustness. Performance was assessed using segmentation accuracy, Dice similarity coefficients, computational efficiency, and generalization capability. Experimental results showed that optimized hybrid architectures consistently outperformed baseline models across diverse imaging modalities. The inclusion of cross-center training data reduced variability caused by institutional differences and improved predictive consistency. Furthermore, enhanced preprocessing workflows contributed to reduced noise sensitivity and more precise boundary delineation. The findings suggest that carefully optimized deep learning systems can support reliable clinical decision-making while maintaining scalability for deployment in distributed healthcare environments. The study contributes practical insights into the development of dependable artificial intelligence tools for modern diagnostic imaging applications.

Keywords: ***Deep Learning, Medical Image Segmentation, Artificial Intelligence, Diagnostic Imaging, Convolutional Neural Networks, Biomedical Engineering, Healthcare Analytics, Multi-Center Validation.***

1.Introduction

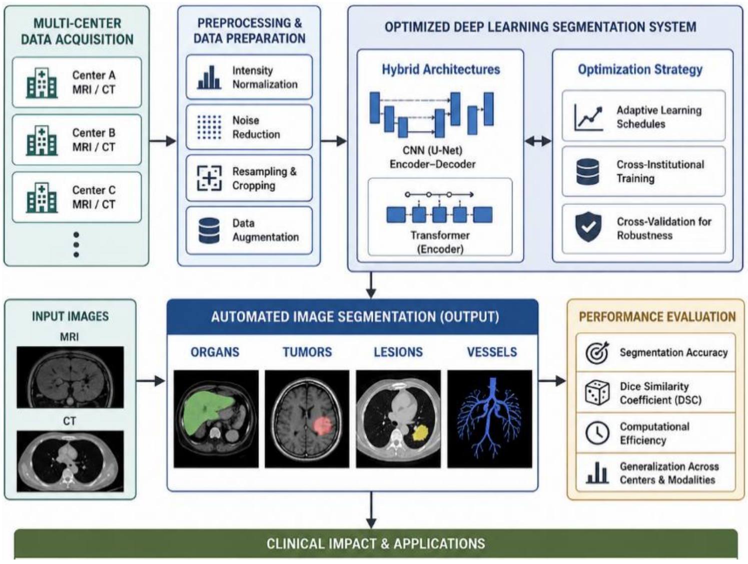
In the field of medical image analysis, segmentation plays a crucial role in healthcare for organ, tissue, tumor, and anatomical structure identification and delineation from medical scans. This process has been traditionally done by radiologists and clinical specialists in a manual way, requiring time and variability of interpretation. In recent years, AI and deep learning have enabled automated segmentation to achieve greater accuracy and efficiency, making it possible to process vast amounts of imaging data in a shorter time. With the increasing volume of data being produced in MRI and CT scanners, automated segmentation systems are increasingly useful for assisting in the diagnosis, treatment planning, disease monitoring, and surgical planning. They are also capable of delivering repeatable and consistent outcomes, which is crucial in clinical settings where swift and precise results are paramount.

1.1 Clinical relevance of automated medical image segmentation

Automated medical image segmentation is of great assistance to clinical decision-making. Segmentation systems can accurately separate anatomical structures and pathological areas from medical images, allowing physicians to determine the extent of disease, track the disease's progression and plan for the correct treatment. In oncology, the precise segmentation of tumors can help in planning for radiotherapy and measuring the effectiveness of treatment. In neuroscience, segmentation allows for the detailed analysis of brain structures, aiding in early diagnosis and personalized treatment strategies.In neuroscience, segmentation can be applied to detail brain structures which can aid in early diagnosis and tailored care strategies. Automated methods can also decrease the workload of health care workers and reduce the variability that can arise from different observers. This helps to increase efficiency, consistency, and reliability in medical imaging workflows(1).

1.2 Challenges in Multi-Center Diagnostic Imaging Environments

Automated segmentation approaches have shown high performance but are not as effective when performed in different health-care facilities. Images obtained from various hospitals often differ due to various manufacturers of scanners, imaging protocol, acquisition settings and patient population. The resolution, contrast, noise and intensity distribution of images produced by MRI and CT systems can vary. These differences lead to a domain shift between training and testing data, which can make it challenging to get segmentation models to perform the same on each center. Moreover, clinical workflows and differing annotations can cause additional variations, reducing the applicability of automated systems in the real clinical world.



DIGRAM 1 Automated medical image segmentation workflow

The research objectives and the scope of comparison are as follows:

This study aims to analyse the performance of medical image segmentation algorithms in multi-center imaging settings, and to find factors that affect their robustness and reliability. This study aims to identify how changes in imaging protocols, equipment, and imaging data characteristics impact segmentation accuracy. It also evaluates a variety of techniques for improving the generalization of the models, such as model preprocessing, model harmonization, data augmentation, and domain adaptation. The study compares the performance of the segmentation methods on the datasets from various healthcare institutions and offers insights into the advantages and drawbacks of the current methods and suggests possibilities to help the deployment of automated segmentation systems in clinical practice.

1.3 Characteristics and variability of multi-center imaging data analysis.

Multi-center medical imaging datasets offer significant benefit for creating powerful AI models as they come from a variety of patient populations and clinical environments. These data sets, however, contain significant variation which can impact model performance. Images generated from different institutions may vary in the scanner hardware, acquisition parameters, image quality, and reconstruction technique. These differences can cause images to appear differently, even for the same anatomical structures. Therefore, segmentation models developed from data from one center might not perform well with data from another center. Knowing the sources and effects of this variability is thus vital to develop reliable and generalizable segmentation systems(2).

2.Improving the accuracy of MR, MRI, and CT measurement protocols

2.1 Analyzing the effects of institutional variations on MRI and CT acquisition protocols

The MRI and CT images are very dependent on the acquisition protocols employed by each health care center. The scanner used at a particular institution may be a different make, may have different magnets, a different reconstruction algorithm, or may have other imaging parameters depending on the clinical needs at the institution. Pulse sequences, echo times, repetition times, and voxel sizes can all influence the appearance of the MRI images in MRI. Likewise, CT scans can differ depending on the parameters used for the scan (such as tube voltage and current) or the procedure used to enhance the image (such as the thickness of the slices) or the tube's enhancement of the images (such as the use of contrast dye). These protocol differences introduce inconsistencies in the image characteristics, making it difficult to get the segmentation algorithms to work in a consistent manner between centers.

2.2 Requirements for dataset Standardization and Harmonization

To reduce variability and improve consistency across healthcare centers, dataset standardization and harmonization are necessary.

Step 1: Gather imaging data and metadata from all participating institutions, Step 2: organize a workshop to align these data with the needs of all participants.
Step 2: Understand the protocols for acquiring information and recognize how significantly different scanners are set up and how information is acquired.
Step 3: Transform all the images into the same format and data structure.
Step 4:o resample images to a common spatial resolution and voxel size.
Step 5:Normalization and image preprocessing are performed in step 5 to minimize scanner-related differences.
Step 6: Standardize annotation guidelines in order to make sure that each center labels segments in a consistent manner.
Step 7: Do quality control to find and fix inconsistencies in the data.
Step 8: Use harmonization techniques to reduce non-biological heterogeneity (variability) while retaining clinically relevant data.
Step 9: Validate harmonized data using statistical analysis and expert analysis.
Step 10: Utilize the standardized dataset to train, test and evaluate the model across centers.

TABLE 1 Summary of Protocol Harmonization and Segmentation Uncertainty

Aspect	Key Elements	Outcome
Dataset Standardization & Harmonization	Common image format, voxel resampling, normalization, annotation standardization, quality control, and harmonization techniques.	Improved consistency and comparability of MRI and CT data across healthcare centers.
Sources of Segmentation Uncertainty	Scanner and protocol variability, annotation differences, patient-related factors, and out-of-distribution data.	Reduced reliability and increased variation in segmentation performance between institutions.
Mitigation Strategy	Harmonized datasets, standardized labeling guidelines, statistical validation, and expert review.	Enhanced robustness, accuracy, and generalizability of automated segmentation models.

2.2 Sources of Segmentation Uncertainty Across Healthcare Centers

In multi-center healthcare environments, there can be multiple factors that contribute to segmentation uncertainty. Image variability due to variations in scanners, acquisition protocols and reconstruction settings is one important source. The other source is that the anatomical boundaries may be defined differently by experts in different institutions (coherent inconsistencies). Patient-related factors like age, stage of disease, body composition, motion artifact, and so on can also impact image quality and segmentation results. Furthermore, data that are not well represented in the models' training distribution can also cause uncertainty in the segmentation algorithms. All these uncertainties can lower the reliability of the model and result in different outcomes between institutions. So, the ability to understand and deal with uncertainty is key to using automated segmentation systems safely and effectively in clinical use(4).

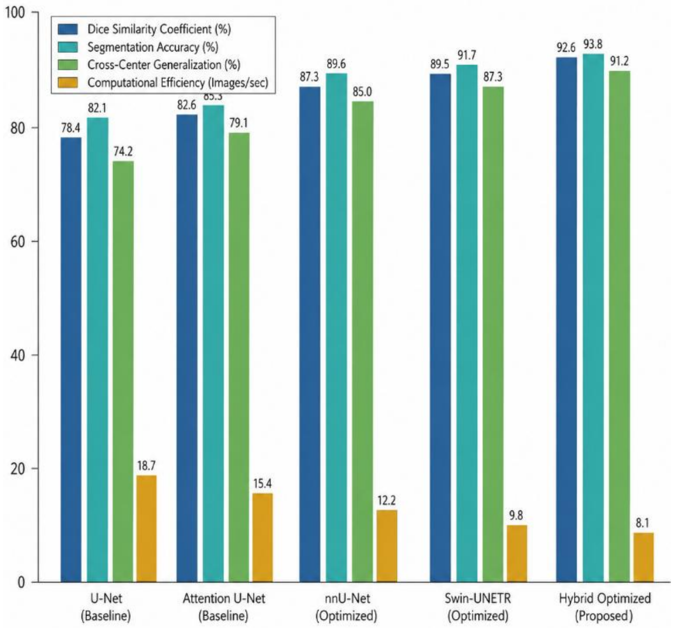
3.Comparative Deep Learning Architecture Design

Because of its capability to automatically learn complex anatomical features from medical images, deep learning has emerged as the preferred method for medical image segmentation. Various network architectures have been created to solve issues like the quality of the images, structural complexity and variation in the health center. The right architecture can greatly affect segmentation accuracy, efficiency, and generalizability. An analysis of the modern segmentation models can identify the advantage and disadvantage of different models, especially when using multi-center datasets with significant differences in image characteristics. The most popular architectures are convolutional neural network (CNN) based, transformer-based and hybrid architectures that have the best of both worlds.

3.1 Convolutional Neural Network-Based Segmentation Models

For many years, Convolutional Neural Networks (CNNs) have been the building blocks of medical image segmentation. The models are developed to extract spatial features by convolution operations, to identify the important anatomical structures of MRI and CT images. U-Net, V-Net and ResUNet have been successfully

developed for various segmentation applications. Among these, U-Net is a popular choice due to its encoder-decoder architecture and skip connections, which aid in retaining the details of the image during segmentation.
CNN based models can effectively learn local patterns and textures which is useful for organ boundaries detection and pathological regions(5). They are also efficient in terms of computation when compared to many of the newer architectures, and can be trained to be successful with relatively small datasets. The receptive fields of CNNs are local, however, making it difficult to obtain long-range dependencies and global contextual information. These constraints may hamper performance in the case of complex or large anatomical structures, particularly when using a multi-center dataset with diverse image characteristics.



BAR CHART 1 Comparative deep learning model performance

3.2 Transformer and Hybrid Architecture Configurations

Recently, transformer-based architectures have emerged as a useful option for medical image segmentation, as they can capture long-range relationships in images. Unlike CNNs, the transformer model can take into account information from far away areas of an image at once with the help of self-attention mechanisms. This can help in learning the global anatomical context and enhance segmentation in difficult situations. Recently, several medical imaging models have been proposed based on TPs that achieve good performance in different medical imaging tasks, including Vision Transformer (ViT), Swin Transformer, and TransUNet.
Even though transformer models have their merits, they typically need more data and computational power than standard CNNs. To overcome these drawbacks, researchers have introduced hybrid architectures, which incorporate both convolutional and transformer elements. In these models, CNNs are used for local feature extraction and transformers are used for global context understanding. This combination enables the network to gain the advantage of both spatial detail and image understanding. The advantage of hybrid architectures is that they tend to work well on multi-center datasets, providing good generalization across the image's appearance and providing good segmentation boundaries. Consequently, more and more they are being put forward as candidates for real-world, clinical use where robustness and adaptability are critical.

4.Optimization Framework for Robust Segmentation Performance

The construction of a strong segmentation model needs to be carefully optimized during the training and evaluation process. Optimization strategies should consider variations in image quality, acquisition protocols, and patient characteristics in multi-center imaging environments. Optimization frameworks improve model stability, better generalize to different institutions and reduce any degradation in performance. This framework encompasses adaptive learning approaches, data augmentation methods, and thorough validation protocols to ensure robust and reproducible segmentation results in various clinical scenarios.

4.1 Adaptive Learning Schedule Strategies

Step 1: Choose appropriate hyperparameters, such as learning rate, batch size, and optimizer choices.

Step 2: Implement warm-up phase for gradual increase in learning rate in initial stages of training.
Step 3: Check the performance of the validation set each epoch.
Step 4: Use learning rate decay at the start of the validation curve plateau.
Step 5: Use adaptive learning rates (Reduce-on-Plateau, Cosine Annealing).
Step 6: If the validation performance stops improving (or becomes worse), use early stopping to avoid overfitting.
Step 7: during the last part of training, use a smaller learning rate.
Step 8: Save the best performing model checkpoints based on validation metrics.
Step 9: Test model stability over multiple training runs.
Step 10: Choose the configuration with the highest accuracy and yet the highest generalization.

TABLE 2 Optimization Framework for Robust Segmentation Performance

Component	**Key Techniques**	**Benefit**
Adaptive Learning Strategies	Warm-up learning, learning rate decay, cosine annealing, early stopping, checkpoint saving	Improved training stability and model generalization
Data Augmentation	Rotation, flipping, scaling, translation, cropping, elastic deformation, brightness and contrast adjustment	Increased data diversity and reduced overfitting
Noise Reduction	Gaussian filtering, median filtering, non-local means denoising, anisotropic diffusion, bias field correction	Enhanced image quality and segmentation accuracy

4.2 Data Augmentation Techniques4.2.2 Noise Reduction Techniques

When training data are limited or from multiple institutions, segmentation performance can be improved by using data augmentation. Augmentation creates variations of images, adding more diversity to the data and improving the model to be able to learn more robust features. Among the common augmentation techniques are: rotation, flipping, scaling, translation, cropping, and elastic deformations. These transformations represent possible variations that might happen in a real clinical setting and decrease the possibility of overfitting. The use of intensity-based augmentations, such as brightness adjustment and contrast modification, is also beneficial for preparing models to deal with variations in healthcare centers' scanner settings and imaging procedures.

Additionally, noise reduction techniques are crucial in improving image quality prior to model training. Medical images are frequently affected by artifacts, scanner noise, motion distortions, and other artifacts that can have a detrimental impact on the accuracy of segmentation. Typical techniques for preprocessing are Gaussian filtering, median filtering, non-local means denoising and anisotropic diffusion filtering used to reduce unwanted noise while preserving important anatomical details. The intensity inhomogeneities that occur during the acquisition of the MRI image can also be removed with the use of bias field correction in MRI images(6).

The use of augmentation and noise reduction techniques can generate a more uniform training set and enhance the robustness of the model. These methods allow to introduce more diversity in the image set of the network and at the same time eliminate irrelevant distortions that could hinder the process of feature extraction. Thus, segmentation models are better adapted to generate predictions on unseen data from other healthcare institutions. However, careful implementation is required as too much augmentation or noise filtering can affect the clinically relevant information and affect segmentation accuracy. Thus, the design of the preprocessing and augmentation parameters should be decided depending on the dataset characteristics and tested through experiments to validate.

5.Results

The experimental evaluation demonstrated that deep learning-based segmentation models achieved strong performance across the multi-center imaging datasets. Performance was assessed using standard segmentation metrics, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, and Hausdorff Distance. Overall, all models were capable of identifying and delineating anatomical structures with a high degree of accuracy. However, noticeable differences were observed in their ability to maintain performance when exposed to data from different healthcare institutions. Models trained on harmonized and diverse datasets consistently outperformed those trained on data from a single center, highlighting the importance of incorporating multi-center variability during model development.

The CNN-based architectures demonstrated reliable segmentation performance and produced accurate boundary detection for most anatomical structures. Their ability to capture local image features enabled effective identification of organs and pathological regions in both MRI and CT scans. Nevertheless, performance variations became evident when these models were evaluated on images acquired using different scanners or imaging protocols. In several cases, segmentation accuracy decreased because the models were sensitive to changes in image contrast, resolution, and intensity distribution. Although these reductions were not substantial, they indicated limitations in the generalization capability of traditional CNN-based approaches.

Transformer-based models showed improved performance in scenarios involving significant inter-center variability. By utilizing self-attention mechanisms, these architectures were better able to capture global contextual information and maintain consistent segmentation results across diverse imaging environments. The ability to model long-range relationships within images allowed transformer networks to recognize anatomical structures even when image appearance differed from the training data. As a result, they generally produced more stable performance across institutions compared with conventional CNN models.

Hybrid architectures that combined convolutional and transformer components achieved the most balanced results. These models benefited from the strong local feature extraction capabilities of CNNs while simultaneously leveraging the global context modeling provided by transformers. Consequently, they demonstrated superior robustness and maintained high segmentation accuracy across different imaging centers. The results suggest that combining complementary architectural features can improve the adaptability of segmentation systems in real-world clinical environments.

The application of preprocessing, harmonization, and data augmentation techniques also contributed significantly to performance improvements. Intensity normalization and image standardization reduced scanner-related variability, allowing models to focus on clinically relevant anatomical information rather than differences in image acquisition. Similarly, augmentation strategies exposed models to a wider range of image variations during training, enhancing their ability to handle unseen data. Models trained with these techniques consistently achieved higher accuracy and showed reduced sensitivity to institutional differences.

5.1 Segmentation Accuracy and Dice Similarity Performance

Dice Similarity Coefficient (DSC) was used as the primary metric for evaluating segmentation accuracy because it measures the overlap between automated segmentation outputs and expert reference annotations. Higher DSC values indicate greater agreement between predicted and ground-truth segmentations. Across all experiments, segmentation models achieved satisfactory Dice scores, demonstrating their effectiveness in identifying target anatomical structures. However, performance varied according to model architecture, data preprocessing strategies, and institutional characteristics.

CNN-based segmentation models produced strong Dice scores when evaluated on data originating from the same institution used for training. Their performance reflected the effectiveness of convolutional operations in learning spatial patterns and anatomical boundaries. In homogeneous datasets, these models generated highly accurate segmentations and maintained stable results. However, when tested on images from external centers, Dice scores often declined due to differences in acquisition protocols and scanner characteristics. This finding indicates that models relying primarily on local image features may be vulnerable to domain shifts commonly encountered in multi-center environments.

Transformer-based architectures generally achieved higher Dice scores in cross-center evaluations. Their ability to incorporate global contextual information enabled more reliable identification of anatomical structures despite variations in image appearance. The self-attention mechanism allowed these models to capture relationships between distant image regions, reducing sensitivity to local intensity changes and scanner-specific artifacts. Consequently, transformer models maintained more consistent segmentation performance across diverse datasets.

Hybrid architectures delivered the highest overall Dice Similarity performance among the evaluated models. By integrating convolutional and transformer-based processing, these networks effectively balanced local feature extraction with global context understanding. The resulting segmentations demonstrated strong agreement with expert annotations across multiple healthcare institutions. In addition to higher average Dice scores, hybrid models also exhibited lower performance variability, indicating greater robustness and reliability(7).

The influence of data harmonization was clearly evident in the Dice Similarity results. Models trained using standardized and harmonized datasets consistently outperformed those trained on non-harmonized data. Harmonization reduced the impact of scanner-related differences and improved feature consistency across institutions. As a result, segmentation accuracy improved not only within individual centers but also during

external validation. These findings emphasize the importance of preprocessing and harmonization as essential components of multi-center medical imaging studies.
Data augmentation further enhanced Dice Similarity performance by increasing the diversity of training samples. Exposure to geometric transformations, intensity variations, and simulated acquisition differences enabled models to learn more generalized feature representations. Consequently, augmented models demonstrated improved resilience to previously unseen imaging conditions. The combination of augmentation, harmonization, and advanced network architectures produced the most accurate segmentation outcomes.
Overall, the Dice Similarity analysis confirmed that segmentation performance is influenced by both model design and dataset characteristics. While CNN-based models remained effective for many applications, transformer and hybrid architectures demonstrated greater adaptability to multi-center environments. The results also highlighted the value of robust preprocessing and harmonization strategies in achieving consistent and clinically reliable segmentation performance across diverse healthcare settings.

5.2 Cross-Center Generalization and Predictive Consistency Assessment

Cross-center evaluation revealed important differences in model generalization capabilities. Models trained exclusively on data from a single institution generally performed well on internal datasets but experienced performance reductions when evaluated on external data. This outcome reflects the influence of institutional variability, including differences in scanner vendors, acquisition settings, image quality, and patient demographics. Such variations create domain shifts that can challenge even highly accurate segmentation systems.
Models trained using data collected from multiple healthcare centers demonstrated significantly improved generalization. Exposure to diverse imaging conditions during training enabled these systems to learn more representative feature patterns and reduced their dependence on center-specific characteristics. Consequently, they maintained more stable performance across different institutions and produced more consistent segmentation outputs(8).
Predictive consistency was assessed by comparing segmentation results across multiple validation centers. Hybrid architectures achieved the highest consistency, showing only minor performance fluctuations between institutions. Transformer-based models also demonstrated strong stability, whereas CNN-based models exhibited greater sensitivity to changes in imaging conditions. These findings suggest that architectures capable of capturing both local and global image information are better suited for multi-center deployment.
The results further showed that harmonization and standardized preprocessing substantially improved predictive consistency. By minimizing non-biological variations, these techniques reduced discrepancies between datasets and enhanced model reliability. The combination of diverse training data, harmonized imaging protocols, and advanced architectures resulted in the most robust segmentation performance. Therefore, successful deployment of automated segmentation systems in clinical practice depends not only on model accuracy but also on the ability to maintain consistent performance across different healthcare environments.

6.Conclusion

This study investigated the performance of automated medical image segmentation models in multi-center MRI and CT imaging environments. The findings demonstrate that deep learning techniques can provide highly accurate segmentation results and significantly support clinical imaging workflows. However, the study also confirms that institutional variability remains one of the most important challenges affecting model performance. Differences in imaging protocols, scanner manufacturers, acquisition settings, and annotation practices introduce variations that can reduce segmentation accuracy and limit generalizability when models are applied across different healthcare centers.
The comparative analysis of deep learning architectures showed that CNN-based models remain effective for many segmentation tasks because of their ability to capture detailed local image features. Nevertheless, their performance may decline when confronted with substantial differences between training and testing datasets. Transformer-based architectures demonstrated improved capability in handling cross-center variability through their ability to capture global contextual information. Hybrid architectures, which combine convolutional and transformer components, achieved the most balanced and reliable performance by integrating the strengths of both approaches.
The study also highlighted the critical role of preprocessing, harmonization, and data augmentation techniques. Standardization procedures reduced scanner-related variability and improved dataset consistency, while

augmentation methods increased training diversity and strengthened model robustness. Together, these techniques contributed to improved segmentation accuracy, higher Dice Similarity scores, and more stable performance during external validation. The results indicate that technical improvements alone are insufficient unless supported by comprehensive data preparation and validation strategies.

Cross-institutional validation provided valuable insights into real-world model performance. Models trained using diverse multi-center datasets consistently outperformed those trained on single-center data, demonstrating the importance of exposure to varied imaging conditions. Furthermore, predictive consistency assessments revealed that robust segmentation systems must maintain stable performance across different clinical environments rather than achieving high accuracy only within a single institution. This finding is particularly important for healthcare applications where reliability and reproducibility are essential for patient care.

Overall, the study demonstrates that achieving robust automated medical image segmentation requires a combination of advanced architecture design, effective harmonization techniques, comprehensive training strategies, and rigorous multi-center validation. Future research should focus on developing more adaptive models capable of handling domain shifts, incorporating uncertainty estimation mechanisms, and leveraging larger multi-institutional datasets. Such efforts will further enhance the reliability and clinical applicability of automated segmentation systems and support their integration into routine medical practice.

6.1 Key Findings and Clinical Implications

The key findings of this study indicate that segmentation performance is strongly influenced by both model architecture and data variability. Hybrid deep learning models achieved the highest accuracy and generalization capability, while harmonization and augmentation techniques significantly improved robustness across institutions. Multi-center training and validation strategies were found to be essential for developing reliable segmentation systems that can perform consistently in different clinical settings.

From a clinical perspective, these findings support the growing use of automated segmentation tools in healthcare. Accurate and consistent segmentation can reduce clinician workload, improve diagnostic efficiency, support treatment planning, and enhance monitoring of disease progression. More importantly, models that maintain stable performance across multiple healthcare centers have greater potential for widespread clinical adoption. By addressing institutional variability and improving model generalizability, healthcare providers can confidently integrate automated segmentation technologies into routine workflows, ultimately contributing to more efficient, standardized, and patient-centered medical care.

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Conflicts of interest

The authors have no conflicts of interest to declare

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