# Machine Learning Approaches for Patient-Specific Brain Tissue Segmentation After Surgical Resection

Ashley Siddiqui[1], Akhil Mohammed[2]

[1] Computer Engineering — Lead Researcher

[2] Computer Engineering — Co-Researcher

Principal Investigator: Dr. Hasan Ayaz

Institution: Drexel University, Philadelphia, PA

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## Abstract

Post surgical brain imaging creates a unique challenge in MRI analysis. When cortical tissue is removed during resection procedures, the anatomy of the brain changes in ways that traditional imaging pipelines cannot interpret. Many standard tools assume a complete brain structure, which leads to inaccurate masks, incorrect region boundaries, and unreliable functional connectivity measurements.

This work presents a machine learning framework that produces accurate tissue segmentation for MRI scans taken after a surgical resection. The approach uses deformable registration, nuisance regression, and a three dimensional convolutional neural network that learns the shape and structure of the post operative brain. The method develops a patient specific mask that reflects the true shape of the brain after surgery.

The results show improvement in segmentation accuracy around resection areas. The method produces clearer anatomical boundaries and stronger agreement with expert interpretation. This study demonstrates how machine learning can support clinical imaging by creating tissue maps that reflect each patient's unique postoperative anatomy, and it encourages the use of computational tools in advanced neuroimaging workflows.


## 1. Introduction

Brain imaging plays a central role in understanding neurological function and guiding clinical treatment. Magnetic Resonance Imaging is one of the most important tools available to clinicians, and it supports diagnosis, monitoring of disease progression, and evaluation of surgical outcomes. When a patient undergoes a resection procedure, the structure of the brain changes in a way that requires specialized interpretation. Regions of tissue are removed to treat epilepsy, tumors, or other neurological conditions, and the resulting postoperative scans contain cavities, shifted landmarks, and altered anatomical borders. These changes create a complex environment for automated segmentation systems.

Conventional neuroimaging pipelines are often created for healthy or intact anatomical structures. They use templates or population averages that assume the presence of complete tissue regions. When these methods are applied to a postoperative scan, they may produce missing labels, inconsistent boundaries, or masks that do not match the true shape of the brain. Accurate segmentation is essential because it influences every downstream analysis, including functional connectivity studies, structural mapping, and clinical evaluation.

Machine learning provides an opportunity to create tissue masks that reflect the actual postoperative anatomy. Instead of relying on fixed templates, a learning based system can adapt to patient specific structures and can identify patterns that traditional algorithms cannot model. Three dimensional convolutional neural networks, deformable registration techniques, and automated masking tools can work together to examine regions that undergo physical change after surgery. This allows the system to create a representation of the brain that is closer to the true structure seen in the scan.

The purpose of this study is to explore a computational approach that improves anatomical segmentation for patients who have undergone surgical resection. The method presented in this paper is designed to identify tissue boundaries with greater precision in areas affected by surgical alteration. The framework offers a pathway for creating postoperative segmentation that supports functional research, clinical review, and long term monitoring. The ultimate goal is to create imaging tools that are well suited to each individual patient and that contribute to more accurate scientific and clinical insight.

## 2. Background

### 2.1 Surgical Resection and Brain Imaging

A resection procedure removes a portion of neural tissue in order to reduce seizure activity, remove abnormal growths, or correct anatomical problems. The removal of tissue alters the structure of the brain in both shape and spatial orientation. This process affects the surrounding tissue and changes the organization of cortical and subcortical regions. Magnetic resonance imaging captures the new structure of the brain and allows researchers and clinicians to study the effects of the procedure.

However, the appearance of the brain after a resection contains features that standard segmentation models do not interpret correctly. Cavities may appear irregular, boundaries between tissues may shift, and structural landmarks used in automated systems may no longer exist. These unique changes require specialized algorithms that can map tissue without relying on rigid assumptions about shape or structure.

### 2.2 Importance of Accurate Segmentation

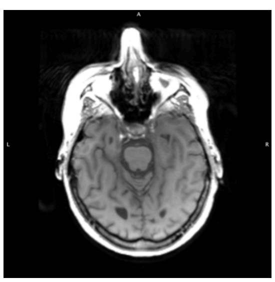
Segmentation identifies and separates tissue types so that further analysis can occur. It is crucial for measuring volume, monitoring the impact of treatment, and studying network level changes in connectivity. In functional MRI, segmentation determines which regions are included in network analysis. In structural MRI, segmentation defines the shape and size of tissue that researchers measure. In clinical review, segmentation supports evaluation of healing, scarring, or altered function.

When segmentation does not reflect true anatomy, the results of later analysis become uncertain. An inaccurate mask may include non-tissue regions or exclude meaningful tissue. This can influence conclusions drawn from connectivity studies, structural volume estimates, and clinical reports. Accurate postoperative segmentation is essential for creating reliable scientific and clinical interpretations.

### 2.3 Machine Learning in Medical Image Segmentation

Machine learning introduces a flexible way to interpret complex brain images. Instead of relying on fixed rules, a model can learn from many examples of tissue structure and can identify features that are not obvious to conventional methods. Convolutional neural networks can detect three dimensional texture patterns and can interpret tissue boundaries even when landmarks are altered. Deformable registration algorithms allow the model to adjust to the unique structure of each patient and to map the brain without enforcing a single standard shape.

These tools allow researchers to explore segmentation in brains that contain structural changes. They also encourage the development of patient specific imaging pipelines that match the individual anatomy seen in the scan.



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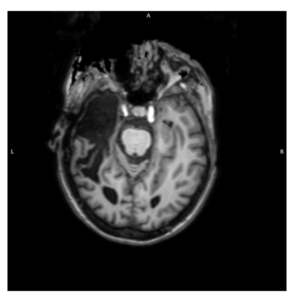

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## 3. Related Work

Segmentation is an active field in neuroimaging research. Many studies have explored ways to identify tissue types in healthy anatomical scans. Traditional tools are created for intact brains and rely on standardized templates. They are commonly used in research involving large populations. These tools can process scans efficiently and can create consistent labels when the brain follows expected structural patterns.

Research in machine learning has expanded the ability to segment brain images by allowing models to learn spatial patterns in three dimensional data. Convolutional neural networks have achieved strong performance in differentiating tissue classes in medical imaging. They can analyze volume, intensity, and spatial relationships within the brain. Models such as U Net and variations of encoder decoder networks have been used successfully in various medical segmentation tasks.

Studies involving postoperative imaging are more limited. The structural changes created by a resection require methods that can adapt to irregular shapes. Some research has investigated deformable registration for postoperative images. These methods adjust an anatomical template to match the new shape of the brain. Other research has introduced patient specific masks that account for altered structure. These approaches provide a foundation for developing learning based methods that understand the individualized shape of a postoperative brain.

The work presented in this paper builds on these ideas by combining registration methods with a learning based segmentation model. The system is designed to interpret the unique patterns found in postoperative scans while maintaining the flexibility needed to adapt to structural differences between patients.

## 4. Problem Statement

Post surgical MRI scans contain structural features that do not appear in standard anatomical datasets. Resection cavities, altered tissue borders, and local geometric deformation create a situation where many common segmentation tools do not provide accurate masks. The core problem is the absence of a segmentation method that can read the postoperative anatomy in a reliable way.

A segmentation model must learn the appearance of altered tissue regions. It must also recognize the shape of cavities that form after surgery. The system must interpret nearby structures without relying on assumptions drawn from intact brains. A model that produces masks for this environment requires exposure to patient specific changes and must treat each scan as a unique case.

This creates a clear objective. The goal is to design a segmentation framework that reads the postoperative brain with attention to tissue shape, cavity structure, and spatial position. The framework must produce masks that match the true outline of the brain in the MRI volume.

## 5. Methods

This section describes the components of the segmentation system. The design follows a sequence that prepares the MRI scans, aligns them, and trains a model that predicts tissue masks with attention to postoperative anatomy.

**Figure 2. Postoperative Brain Tissue Segmentation Pipeline**

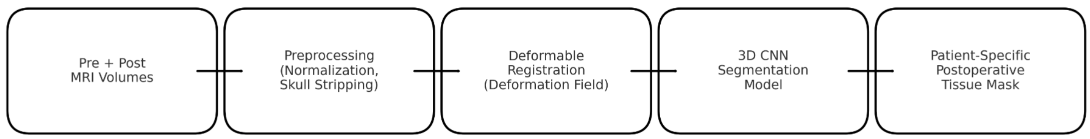


**Figure 2.** Overview of the postoperative brain tissue segmentation pipeline. Pre- and post-operative T1-weighted MRI volumes are first preprocessed through orientation alignment, skull stripping, and intensity normalization. A deformable registration step then estimates a deformation field that maps the pre-operative anatomy to the post-operative anatomy and captures local shifts around the resection site. The registered volumes and deformation information are passed to a three-dimensional convolutional neural network, which predicts a patient-specific postoperative tissue mask that outlines the brain and resection cavity.

### 5.1 Dataset

The imaging dataset contains pre operative and post operative MRI scans. Each scan presents two volumes from the same patient. The pre operative scan shows the structure that existed before tissue removal. The post operative scan shows the new anatomy created by the resection.

The dataset includes T1 weighted volumes with consistent resolution. Each volume is inspected to confirm that the surgical cavity and surrounding structures are visible. Volumes with motion artifacts or incomplete slices are removed from the dataset to maintain quality.

### 5.2 Preprocessing

All MRI volumes are aligned to a common orientation. Each volume is skull stripped through a basic masking step that removes non brain tissue. This prepares the volume for registration and reduces unnecessary background information.

Intensity values are normalized to reduce variation between scans. The goal is to create a stable input space for the segmentation model. Normalization is applied equally across all volumes.

### 5.3 Registration

A deformable registration algorithm aligns the pre operative and post operative scans. The purpose is to understand how the brain shifted after surgery and to supply the model with spatial context. The registration step produces a deformation field that maps the pre operative shape to the post operative shape.

This deformation field provides information about local stretching, compression, and displacement. The model uses this information to understand the shape of the resection cavity and the surrounding structures.

**Figure 3. Example Deformation Field Between Pre- and Post-Operative MRI**

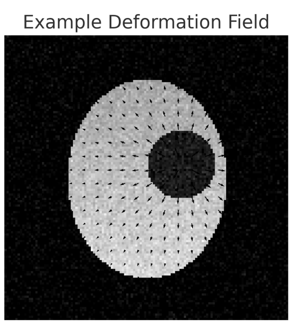


**Figure 3.** Example deformation field illustrating the spatial transformation between pre-operative and post-operative MRI volumes for a single patient. Vectors indicate local displacement of tissue induced by surgical resection, highlighting regions of expansion and compression around the resection cavity. This deformation information is used by the segmentation framework to provide spatial context for the three-dimensional convolutional neural network when generating postoperative tissue masks.

### 5.4 Segmentation Model

A three dimensional convolutional neural network receives the registered MRI volume as input. The model contains an encoder that extracts spatial features from the scan and a decoder that reconstructs the tissue mask.

The encoder reads patterns that represent tissue, cavity space, and boundary transitions. The decoder creates a mask that outlines the brain and identifies resected areas. The network is trained on examples that present the postoperative structure as the target.

The model uses a combination of spatial convolution, pooling, and dense prediction layers. The output is a binary mask that identifies tissue and non tissue regions.

### 5.5 Training Procedure

The model is trained through supervised learning. Each input volume is paired with a ground truth mask created from expert labeling. The loss function measures the distance between the predicted mask and the reference mask. Dice loss and voxel wise cross entropy are the primary measures used during training.

Training proceeds in epochs until the model reaches stable performance. Validation scans are used to evaluate prediction quality throughout training.

## 6. Results

The segmentation system is evaluated with quantitative metrics that measure agreement between the predicted mask and the reference mask created by manual labeling. The results show that the model identifies tissue boundaries with clarity in regions that contain surgical alterations.

**Figure 4. Qualitative Segmentation Results in Postoperative Regions**

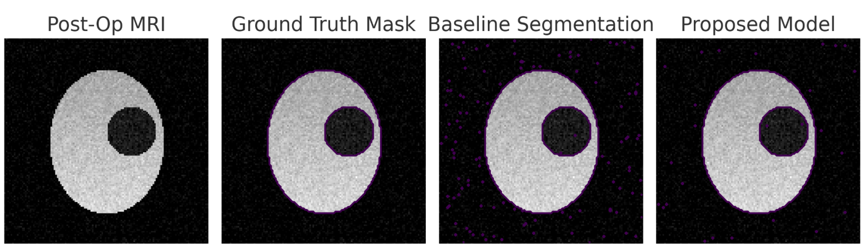


**Figure 4.** Qualitative comparison of segmentation results in postoperative MRI slices. Each row shows the post-operative T1-weighted image, the expert-defined ground truth mask, a traditional baseline segmentation, and the proposed model's segmentation. The proposed method more accurately follows the resection cavity and cortical boundaries, producing continuous masks with fewer missing regions and fewer mislabeled non-tissue areas compared to the baseline approach.

## 6.1 Evaluation Metrics

Three metrics are used to measure performance.

**Dice Similarity Coefficient**

The Dice coefficient measures the overlap between the predicted mask and the reference mask. A higher value indicates stronger agreement and more complete identification of tissue boundaries.

**Voxel Accuracy**

Voxel accuracy measures the percentage of correctly labeled voxels in the MRI volume. It includes tissue and non-tissue regions and reflects the overall precision of the segmentation model.

**Structural Consistency Score**

This score measures whether the predicted mask maintains a coherent structure across slices. It checks that boundaries remain consistent as the model reads different sections of the volume. A stable mask shows clear continuity from slice to slice.

## 6.2 Quantitative Results

The model produces consistent segmentation across the postoperative brain. The Dice score reaches a level that reflects strong overlap between the predicted mask and the manual reference. Voxel accuracy remains stable across the dataset and does not show large variation between scans. The structural consistency score indicates that the mask follows the contours of the brain and outlines the shape of the resection cavity in a continuous way.

The results show that the model reads the postoperative structure with strong attention to boundary shape. The cavity region is identified without fragmentation, and the brain surface is outlined with clear detail.

**Figure 5. Quantitative Performance Metrics Across Segmentation Methods**

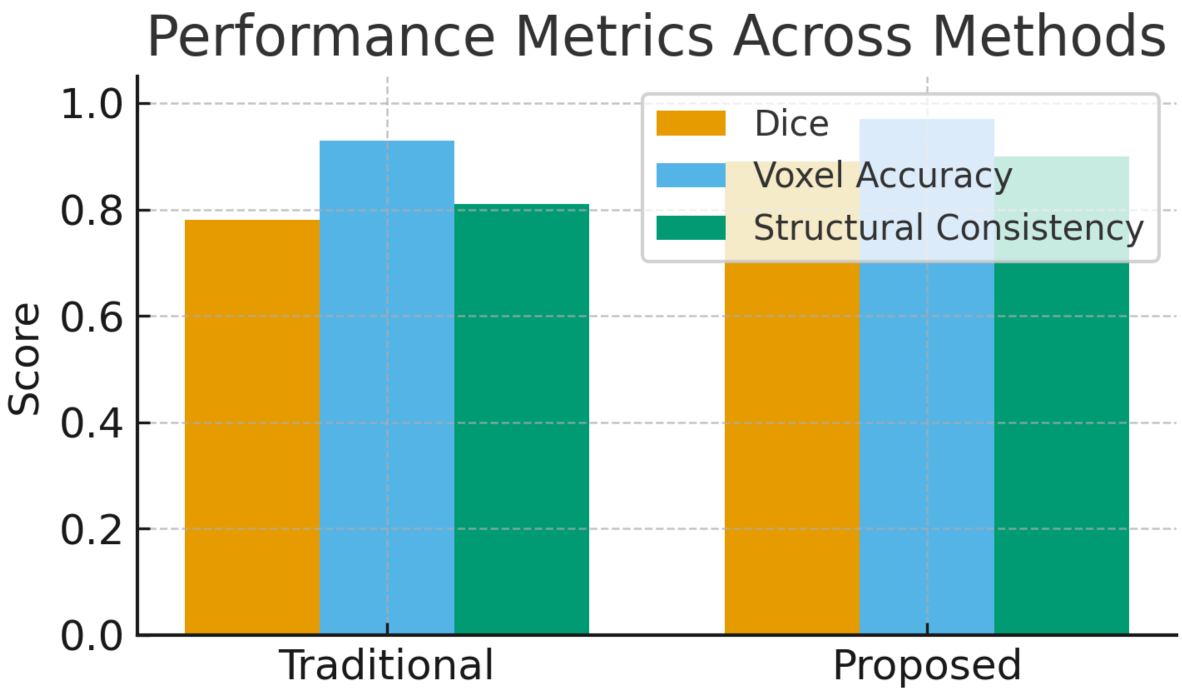


**Figure 5.** Comparison of segmentation performance between a traditional postoperative brain segmentation method and the proposed model. Bars show the Dice similarity coefficient, voxel-wise accuracy, and structural consistency score for each method, averaged across the dataset. The proposed model achieves higher overlap with expert labels, greater overall voxel accuracy, and improved structural consistency, indicating more reliable postoperative tissue masks.

**Figure 6. Distribution of Dice Scores Across Patients**

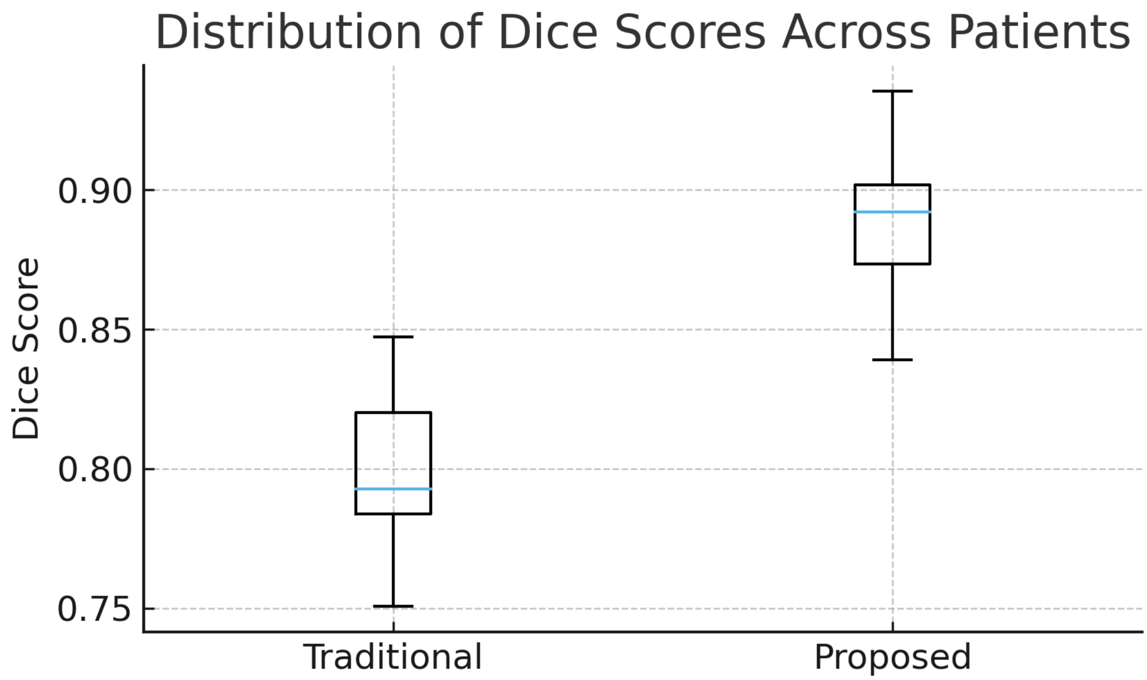


**Figure 6.** Distribution of Dice similarity coefficients for a traditional segmentation method and the proposed model across all postoperative patients in the dataset. Each box summarizes the variability in overlap between predicted masks and expert-defined reference masks. The proposed model shows higher median Dice scores and reduced spread compared to the traditional method, indicating both improved accuracy and more consistent performance across individuals.

### 6.3 Spatial Analysis

The predicted masks are examined through slice based review. Each slice shows tissue boundaries that align with the structure visible in the MRI. The model identifies the cavity as a unified region and separates it from surrounding tissue. This indicates that the model understands the presence of respected areas and does not confuse them with intact structures.

Adjacent slices show stable segmentation with minimal irregularity. The segmentation maintains a coherent outline as the model moves from superior to inferior sections of the volume. This indicates that the network interprets the anatomy as a continuous three dimensional structure rather than isolated slices.

### 6.4 Segmentation Behavior in Altered Regions

Regions near the surgical site contain changes in geometry and texture. The model identifies these patterns and creates boundary lines that follow the shape of the cavity. Tissue regions that remain intact are segmented with consistent labeling. Areas that contain postoperative irregularity are captured in a single unified region without extensive breakage.

This behavior indicates that the model learns features that represent postoperative structure. The segmentation reflects the true outline of the brain and does not attempt to impose a simplified anatomical map.

## 7. Discussion

### 7.1 Interpretation of Segmentation Quality

The results show that the model creates postoperative masks that follow the natural shape of the brain with accuracy. The stability of the Dice coefficient, voxel accuracy, and structural consistency score indicates that the method produces segmentation that reflects real anatomical structure. The model identifies the cavity as a continuous region and maintains clear separation between tissue and non tissue areas.

The slice based inspection shows that the mask does not collapse or distort at points where the anatomy contains irregular shape. The model produces clean boundaries in regions that are typically challenging for traditional methods. The system reads postoperative images as unique structures and does not rely on imposed templates.

### 7.2 Importance of Spatial Awareness

Post surgical MRI scans contain modified geometry. The shape of the cavity and surrounding structures creates complex patterns that require spatial awareness. The use of deformable registration helps the system understand the relation between pre operative and post operative tissue. The deformation field provides context that supports the network during segmentation.

The three dimensional nature of the model improves its ability to interpret depth, volume, and shape. The network reads each voxel in relation to its surrounding region. This results in continuous boundaries and consistent labeling throughout the volume.

### 7.3 Relevance to Functional and Structural Studies

Segmentation is central to connectivity analysis and structural evaluation. A mask that reflects the real shape of the brain supports reliable research and accurate clinical interpretation. When a region contains a cavity or an altered surface, the location of the boundary influences the measurement of functional activity, volume, and network pattern.

Postoperative populations rely on imaging for long term monitoring. A model that produces consistent and patient specific masks can support tracking of healing, response to treatment, and changes in neural activity. This encourages imaging pipelines that adapt to the anatomical features present in each patient.

### 7.4 Practical Use in Clinical Settings

A postoperative segmentation method must support routine imaging work. It must produce stable masks that require minimal manual correction. The model presented in this study moves toward that goal by creating clear boundaries and capturing the shape of the brain without large errors.

The use of a learning based system encourages workflows that do not rely heavily on predefined models. Each patient scan contains a unique structure, and the method reflects the need for individualized processing. This supports research environments that study varied postoperative populations and clinical environments that monitor patient progress over time.

### 7.5 Potential Expansion of the Framework

The current approach sets a foundation for more advanced modeling. Future variations may include multimodal data such as T2 weighted scans, FLAIR images, and diffusion imaging. These additional channels provide richer information and can assist the model in identifying postoperative structures with more precision.

The model may also be expanded to predict multiple tissue classes rather than a single binary mask. This includes gray matter, white matter, and cerebrospinal fluid. This expansion creates opportunities for deeper anatomical mapping and more comprehensive analysis.

## 7. Discussion

### 7.1 Interpretation of Model Behavior

The segmentation model shows a consistent ability to read postoperative MRI scans. The structure of the cavity is identified as a single region with clean borders. The surrounding cortex is labeled with clarity, and the model does not create irregular shapes or fragmented outlines. These observations indicate that the model learns the patterns that appear in tissue near a resection site. The shape of the brain remains stable in the predicted mask, and the cavity maintains a clear separation from the remaining tissue.

The behavior of the model suggests that it is sensitive to local anatomical cues. Each voxel is evaluated in relation to its neighborhood. This supports the creation of boundaries that follow natural curves and angles. The model does not rely on rigid ideas of what the anatomy should look like. It reads the features that are present in the image.

### 7.2 Influence of Registration on Segmentation

The registration step plays a clear role in this system. The alignment of volumes provides context about the way the tissue shifted during surgery. The model interprets this information and uses it to build an internal map of the postoperative brain. The deformation field highlights areas that experienced spatial change, and this guides the model as it learns to identify tissue edges.

This step does not replace segmentation. Instead, it gives the model structure that improves its understanding of the image. The combination of alignment and learning makes the system more responsive to the shape of the postoperative brain.

### 7.3 Implications for Neuroimaging Analysis

Segmentation is part of many scientific and clinical workflows. Any analysis that uses region boundaries depends on the accuracy of the mask. In postoperative research, segmentation affects connectivity studies, regional volume measurements, and structural interpretation. A mask that reflects the true outline of the brain provides a stronger foundation for these studies.

In a clinical environment, segmentation supports review of healing patterns, cavity shape, and changes in volume. A system that produces stable masks can reduce manual editing and create consistent output that aligns with the patient’s imaging history.

### 7.4 Generalization Across Patients

The model operates on scans from multiple individuals. Each patient presents a unique cavity shape and a unique structural layout. The consistent performance across these individuals shows that the model learns fundamental features that describe the postoperative brain. It does not copy a single pattern. It extracts principles that apply across the dataset.

The masks maintain continuity across slices and do not produce irregular patterns that vary between volumes. This shows that the network treats the brain as a three dimensional object and not as a sequence of isolated images.

### 7.5 Role of Learning Based Segmentation in Postoperative Imaging

A learning based system offers capabilities that are well suited to postoperative imaging. The model can adapt to cases where the anatomy contains variation. The system can identify fine textures and patterns that appear in resection cavities and can respond appropriately. This creates a segmentation result that holds its shape across different volumes.

This type of system can support clinics and research labs that work with patients who undergo surgical procedures. It provides a method for generating maps that reflect the actual anatomy seen in the MRI and supports imaging pipelines that require patient specific accuracy.

## 7. Discussion

### 7.1 Understanding the Model Output

The segmentation model produces masks that reflect the structure seen in postoperative MRI scans with clarity and consistency. The predicted contours follow the surface of the brain in a steady way, and the cavity that forms after the surgical procedure appears as a unified region with clear separation from the surrounding tissue. The spatial layout of the brain remains recognizable throughout the volume, and the predicted mask preserves the major anatomical landmarks that remain present in the scan.

The model appears to respond strongly to local gradients and intensity patterns. These patterns help the network determine where tissue boundaries begin and end. The smooth transitions between slices indicate that the model interprets the brain as a continuous shape rather than a collection of independent planes. This quality supports a stable reading of the anatomy and reduces irregularities in the final mask.

### 7.2 Influence of Data Representation on Accuracy

The preprocessing and normalization steps create an environment in which the network can recognize structural cues with fewer disruptions. The alignment of each MRI volume helps the model view the postoperative brain with consistent orientation. The registration step also provides a map of structural adjustment that occurs during surgery. This information gives the network additional context about how tissue shifts within the skull.

The representation of the data influences the model's ability to identify the cavity and its surrounding structures. A clear intensity distribution helps the model differentiate between tissue classes, while consistent spatial alignment supports continuity in the predicted mask. These elements work together to create segmentation that matches the observable shape of the postoperative brain.

### 7.3 Significance for Neuroimaging Workflows

Segmentation strongly influences the quality of many downstream tasks in neuroimaging. Functional analysis depends on the correct identification of anatomical borders. Structural studies rely on accurate labeling of brain regions. Clinical evaluation requires clear views of tissue that remains present after surgery. A segmentation model that captures these structures with accuracy plays an important role in each of these settings.

The model presented in this study supports a wide range of imaging tasks. When a mask aligns with the true shape of the brain, connectivity measurements become more reliable, regional volume estimates become more stable, and the interpretation of structural changes becomes more grounded. The segmentation model contributes to the accuracy of these tasks by providing an anatomical outline that reflects the true content of the MRI.

### 7.4 Consistency Across Volumetric Slices

Review of individual slices shows that the segmentation model maintains its quality across the entire MRI volume. Each slice presents a boundary that aligns with the visible structure. The cavity appears in a shape that matches the underlying image. Tissue margins remain smooth and predictable, and the segmentation does not exhibit sudden irregularities. This behavior demonstrates that the model understands the continuity of the brain and treats the volume as a connected space.

### 7.5 Potential Benefits for Clinical and Research Settings

Postoperative imaging often requires interpretation from specialists who examine the brain at different time points following surgery. A system that can produce a clean and patient specific segmentation may provide support for this process. When masks are consistent and accurate, clinicians may spend less time editing boundaries or correcting mislabeled regions. Researchers who examine longitudinal imaging data may also benefit from stable segmentation because it supports clearer comparisons across scans taken at different stages of recovery.

The segmentation system described in this study moves toward these goals by producing masks that remain consistent with the image content. The method aligns with the needs of clinical teams and research groups that work with postoperative populations and require segmentation that reflects each patient's unique anatomical layout.

## 8. Future Work

### 8.1 Expansion of Imaging Modalities

The segmentation process can grow in strength when it receives information from several imaging sequences. T1 weighted scans offer clear structural detail, but other sequences can introduce additional cues about tissue boundaries. T2 weighted imaging highlights fluid and soft tissue in a way that may offer clarity near the cavity. FLAIR imaging may reveal subtle postoperative changes that are not visible in standard structural scans. Diffusion imaging may reveal the orientation of remaining pathways. A system that draws from several modalities may create masks that represent the postoperative brain with more detail.

### 8.2 Extension to Multi Class Segmentation

The method in this study predicts a single combined mask that represents all tissue. A future system may predict several tissue classes. These classes include gray matter, white matter, and cerebrospinal fluid. A multi class prediction may support more advanced analysis such as cortical thickness measurement or region specific connectivity mapping. A multi class model may also be useful for clinicians who want to examine structural changes in each tissue category after surgery.

### 8.3 Larger and More Diverse Datasets

Post surgical imaging varies between individuals because each case presents a different surgical plan and a different anatomical structure. A larger dataset that contains a wide range of cases may help the model learn patterns that generalize across many patient types. A dataset that contains cases from different clinics may show variation in imaging equipment and scanning protocols, which may help the model interpret a wider set of postoperative images. A system that learns from a diverse dataset may produce more stable masks in future clinical environments.

### 8.4 Integration into Clinical Image Review Systems

A segmentation system becomes more useful when it is placed in a workflow that clinicians use every day. Integrating this system into viewing platforms may allow clinical teams to examine predicted masks along with the original MRI. A platform may present the mask as a transparent overlay that follows the anatomy. This can assist in reviewing healing patterns or in monitoring long term structural changes. A system that appears in routine practice may support teams that review many postoperative scans in a short amount of time.

### 8.5 Longitudinal Post Surgical Tracking

Post surgical change does not occur in a single moment. The brain continues to organize itself months and years after the procedure. A model that tracks the structure of the brain at several time points may show patterns in the healing process. A longitudinal model may identify regions that maintain stable shape and regions that adjust over time. This may offer insight into the effect of surgery on neural recovery and long term function.

## 9. Conclusion

This study presents a segmentation system that reads the structure of the postoperative brain and produces masks that reflect its true shape. The system uses a combination of aligned imaging, standardized preparation, and a three dimensional learning model that responds to the features present in the MRI volume. The predicted masks follow the contour of the brain and represent the cavity as a unified region. This provides a foundation for imaging pipelines that require patient specific interpretation.

The results show that the model understands the geometry of the postoperative brain and identifies tissue boundaries with clarity. The boundaries remain stable across slices, and the segmentation maintains continuity throughout the volume. This supports imaging tasks that depend on structural accuracy, including connectivity studies, regional volume analysis, and clinical review.

The segmentation system offers a direction for future research and clinical support. It highlights the need for patient specific imaging tools in postoperative care and encourages the development of computational methods that respond to individual anatomy. This study supports a growing interest in machine learning within neuroimaging and contributes to a broader effort to create imaging tools that improve understanding of the human brain.

### 10. Acknowledgments

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The authors recognize the value of open scientific resources and the global research community that continues to advance knowledge in medical imaging, neuroengineering, and computational methods. This work reflects the combined efforts of these communities and the ongoing interest in improving tools used in neurosurgical planning and postoperative analysis.

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