

Research Article

3D Magnetic Resonance Image Segmentation Using HD Brain Extraction in 3D Slicer

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Abstract

Applications of image processing in radiology and radiation are critical for the development of models, simulations, and computational tools. 3D Slicer is a widely used platform for processing, segmenting, visualizing, registering, and analyzing medical images, as well as for image-guided treatments. Image segmentation, which focuses on identifying specific regions in the image such as tumors or lesions, is one of the most common challenges in medical image processing. In this research work we have utilized 3D Slicer to implement simulation techniques and automation for imaging diagnostics, computation, and prediction. This paper expands on the HD Brain Extraction module in 3D Slicer to autonomously segment brain MRI images using artificial intelligence. To optimize the brain extraction process, various adjustable parameters including segmentation techniques, threshold values, and smoothing factors are fine-tuned. The brain is then extracted from MRI images for further analysis and visualization.

Keywords: 3D slicer, segmentation, medical images, medical image processing, MRI, brain images.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is a vital technique in medical imaging, offering detailed insights into the anatomy of the human body. In particular, the segmentation of brain structures from MRI data plays a crucial role in clinical and scientific applications, such as brain research, disease detection, and treatment planning [1-4]. Precise brain segmentation enables thorough analysis of brain regions, which is essential for diagnosing and monitoring neurological disorders such as Alzheimer's, multiple sclerosis, and brain cancers [5-7]. Despite the high quality of MRI data, manual segmentation remains a time-consuming, error-prone task that requires expertise and can be particularly challenging when dealing with large datasets.

Recent advancements in machine learning and deep learning have revolutionized medical image analysis by providing powerful tools for automated segmentation. 3D

Slicer, an open-source software platform, is widely used for medical image processing and visualization. Among its many tools, the HD Brain Extraction module stands out as a robust, automated solution for segmenting brain structures from MRI images. Using deep learning models trained on diverse datasets, HD Brain Extraction can segment brain regions from various MRI modalities, including T1-weighted and T2-weighted scans, with high accuracy. The integration of this module within 3D Slicer's user-friendly interface makes it accessible to both researchers and clinicians, simplifying the brain extraction process and enhancing its efficiency.

This article provides a comprehensive guide on how to use the HD Brain Extraction module in 3D Slicer for effective brain MRI segmentation. We offer a detailed methodology to achieve optimal segmentation results, along with an overview of the module's key features and usage requirements. Furthermore, we discuss potential applications of this tool in academic and clinical settings, including suggestions for post-processing techniques to further enhance segmentation quality [8-13].

The rapid advancement of technologies such as artificial intelligence (AI), nanotechnology, and machine learning has significantly impacted the biomedical sciences, particularly in the field of diagnostics [1]. In response to the increasing demand for new scientific technologies and innovative solutions in healthcare, our research group has been focused on developing the AI-driven applications for bioengineering and diagnostics.

The primary goal of our research is to explore novel AI applications in biomedical technology, with a particular focus on enhancing medical imaging diagnostics, computational methods, and predictive modeling. Our work aims to improve diagnostic accuracy, reduce errors, and optimize the efficiency of imaging procedures by integrating AI-based predictive models, simulation techniques, and automation. To achieve this, we focus on developing and refining AI algorithms for medical image segmentation and contouring, using tools such as Pytorch for deep learning and 3D Slicer for segmentation processes [13].

Additionally, we have also conducted extensive research into the current state of AI integration in diagnostic facilities in our country. Through meetings with imaging professionals and visits to public and private hospitals, we have gathered valuable data on the adoption of advanced image processing technologies. It has been created a network of medical imaging experts across the nation and launched the AI4MED project to foster collaboration and share knowledge on the use of AI in medical diagnostics and automation [12].

MATERIALS AND METHODS

Segmentation is a fundamental step in medical image processing, involving the division of an image into distinct regions or segments to identify structures or areas of interest. The primary goal of segmentation is to accurately delineate different anatomical structures within an image, facilitating a more detailed examination and analysis of the medical data [8].

Various segmentation methods are employed in medical image processing, including machine learning-based techniques, region growing, manual segmentation, thresholding, and clustering [9]. The choice of segmentation method depends on the type of medical image, the required precision, and the specific application. While manual segmentation is often considered the gold standard for accuracy, it is labor-intensive, time-consuming, and prone to inter-observer variability. On the other hand, automated methods, while faster and more efficient, may be less accurate and often require validation by a medical expert [9-11].

The HD Brain Extraction module offers significant utility across various clinical and research applications. Accurate segmentation of different brain regions is crucial for studying neurodegenerative diseases such as Huntington's, Parkinson's, and Alzheimer's. In this context, HD Brain Extraction is employed to facilitate volumetric analysis of brain structures, aiding in the tracking of brain atrophy over time. Segmentation also forms the foundation for both anatomical and functional brain mapping. Additionally, in functional magnetic resonance imaging (fMRI), it helps define regions of interest (ROIs) crucial for studying brain activity. Moreover, techniques like diffusion tensor imaging (DTI) can assess the integrity of white and gray matter.

In oncology, HD Brain Extraction plays a pivotal role in tumor segmentation, enabling precise identification and delineation of brain tumors. This capability is essential for measuring tumor size, planning treatment protocols, and monitoring the effectiveness of interventions such as chemotherapy, radiotherapy, and surgery. Additionally, in the fields of artificial intelligence and machine learning, HD Brain Extraction generates high-quality segmented data that can be leveraged to develop novel diagnostic and prognostic tools. The module is also used for automating classification tasks, such as distinguishing between healthy and pathological conditions, as well as for training and validating machine learning models aimed at predicting neurological outcomes.

Figure 1 depicts the implemented high-level view of the 3D Slicer architecture [2].

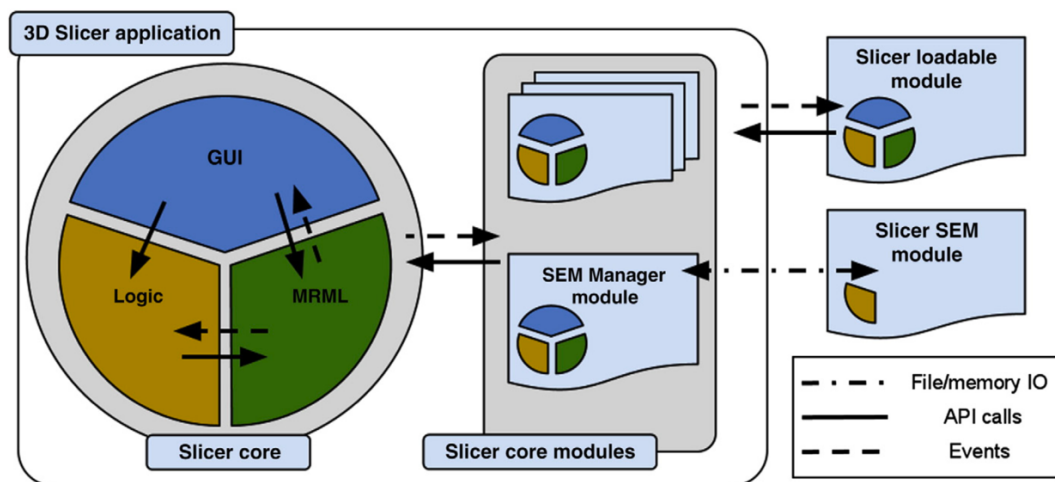


Figure 1. High-level view of the 3D Slicer architecture [2].

It has been employed 3D Slicer to carry out a variety of segmentation procedures, including automated, semiautomatic, and manual segmentation. In this instance, we report a Low-Grade Glioma discovered after an MRI. One patient's MRI scans were imported into 3D Slicer as part of the Brain Tumor Segmentation data, see Figure 2.



Figure 2. Tumour identification on MRI images.

Structures can be identified by a segmentation process that can be done automatically or manually. You can modify labels with 3D Slicer, and then you can merge them once more [8]. In this work, thresholding and a 3D connectivity effect known as "Save Island" were used to alter the tumor (green hue). For each label, the triangulated surface models are thus constructed and the three label volumes are concatenated.

RESULTS

Figure Figures 3 and 4 illustrate the 3D Slicer interface during the segmentation process. In the 3D view, the tumor region is highlighted in green as part of the entire brain structure. Although the tumor volume was segmented in its entirety, the algorithm was initiated on a single slice. Solid colors represent the initial steps of the segmentation procedure. In contrast, the T2-weighted image overlays the segmentation results as a semi-transparent layer. To evaluate the accuracy of human versus machine segmentation, statistical analysis was performed using the P-value and the coefficient of determination (R^2) with a 95% confidence interval [12, 13-15].

To assess the speed and accuracy of the classifiers, several tests were conducted in close collaboration with American Hospital 3 in Tirana. The metrics used to evaluate the diagnostic performance in MRI scans are well-understood by radiologists and technicians. To facilitate broader adoption of this system across various healthcare settings, the detailed procedure will be shared via our platform [2]. On a standard personal computer, the entire segmentation process, as depicted in the screenshots, was completed in approximately five

minutes. However, the use of frameworks such as PyTorch and CUDA could potentially enhance processing speed [14, 16-19]. Furthermore, standard deviations were calculated as a percentage of the average volumes for each of the three structures. The results demonstrate that the segmentation inaccuracies fall within acceptable thresholds, with deviations ranging between 1.5% and 3%.

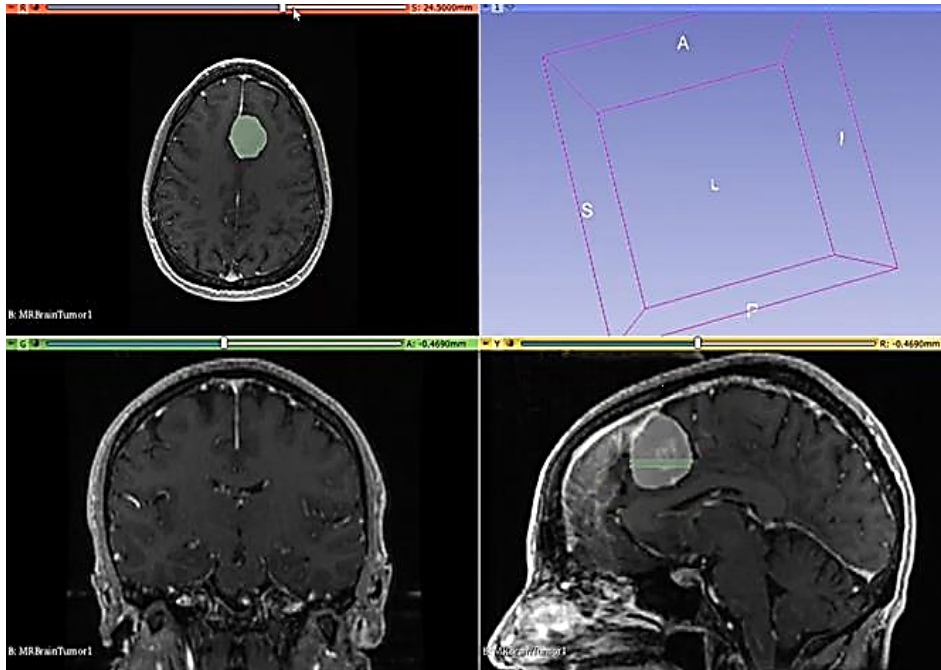


Figure 3. 3D Slicer interface

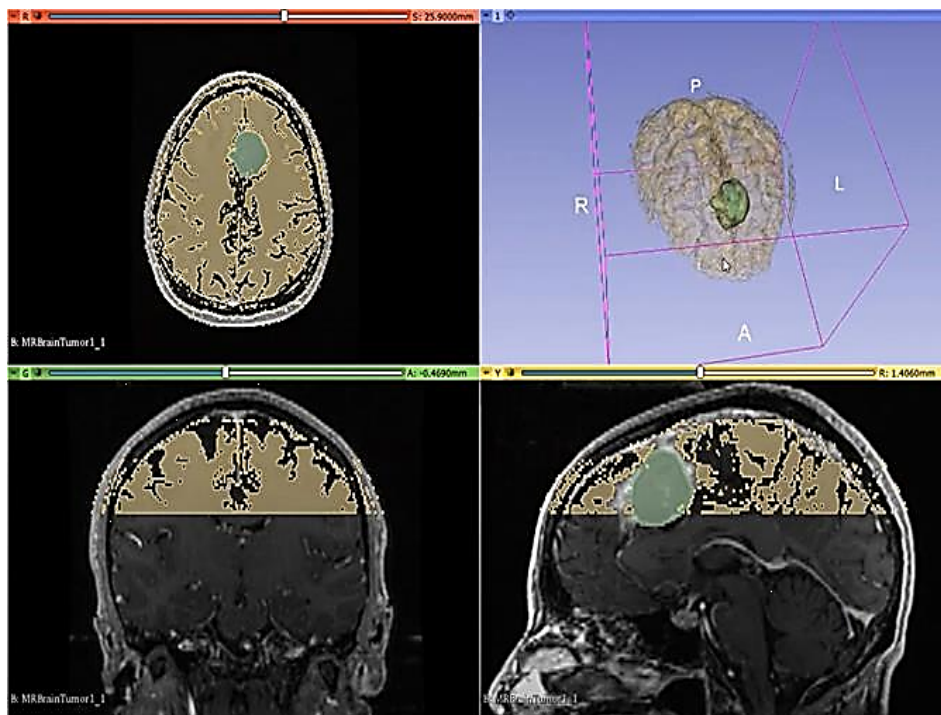


Figure 4. Segmentation using HD Brain Extraction extension in 3D Slicer.

SUMMARY AND CONCLUSION

The HD Brain Extraction tool in 3D Slicer is a powerful integration of advanced deep learning techniques and an intuitive user interface, making it an essential tool in medical imaging. Its current applications hold significant promise for enhancing both clinical procedures and research efforts, ranging from pre-operative planning to the study of neurological disorders.

Looking ahead, the future of HD Brain Extraction is even more promising. As the tool continues to evolve to address emerging challenges in automated healthcare, personalized medicine, and cutting-edge neuroscience, it is poised to play a key role in revolutionizing medical imaging. By bridging the gap between complex imaging data and actionable insights, HD Brain Extraction has the potential to improve patient outcomes while advancing scientific understanding.

This study demonstrates the value of HD Brain Extraction as a critical tool for medical imaging and radiation specialists, using the "Segmentation Toolbox" from 3D Slicer. To illustrate its applicability, a case study of brain tumor MRI segmentation is presented. However, integrating this tool with other segmentation techniques may require additional computational expertise, particularly in the use of advanced algorithms and tools. Our survey findings highlight the challenges faced by medical professionals in regularly performing segmentation, as well as the lack of adequate training for utilizing new technologies and artificial intelligence in diagnostics. Nevertheless, these challenges also present an opportunity for significant improvements in clinical practice, particularly for medical physicists, radiologists, and oncologists.

The rapid segmentation of the brain is a highly valuable feature, offering an efficient model for training and research purposes. Time efficiency is a critical consideration, as automated segmentation methods can reduce the time needed for corrections compared to manual segmentation [14, 20-23]. Additionally, the consistency offered by auto-segmentation provides an advantage, as it ensures uniformity across various medical images. This consistency results in more reliable and accurate outcomes by reducing inter-observer variability that can arise when multiple practitioners segment the same image. Furthermore, the reduced susceptibility to human bias or errors enhances the overall accuracy of segmentation, particularly for complex structures, where machine learning algorithms and other advanced techniques surpass human performance.

Beyond its current capabilities, HD Brain Extraction's potential is vast, driven by the integration of new technologies and multidisciplinary approaches. One of the most promising future applications is personalized medicine, where HD Brain Extraction can provide tailored brain maps for targeted treatments. Additionally, the tool could play a key role in telemedicine and remote healthcare by enabling automatic, real-time segmentation on cloud-based platforms. This would not only facilitate large-scale, cross-population studies on brain structural diversity and neural adaptability but also advance our understanding of brain function and cognition.

Further integration of HD Brain Extraction with AI-driven decision support systems could enhance clinical workflows by assisting radiologists with automated anomaly detection, providing real-time segmentation results during surgeries, and speeding up diagnostic processes through instant analysis [24-27].

As imaging and computational techniques continue to develop, the future of HD Brain Extraction is bright. Its ongoing evolution promises to expand its impact in both scientific research and clinical healthcare, offering exciting possibilities for improving diagnostics and treatment planning.

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CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest associated with this publication.

REFERENCES

1. Boddu, R. S. K., Karmakar, P., Bhaumik, A., Nassa V.K., Vandana, Bhattacharya, S. Analyzing the impact of machine learning and artificial intelligence and its effect on management of lung cancer detection in COVID-19 pandemic. *Materials Today: Proceedings*, **2022**; 56; 2213–2216.
2. Fedorov, A., Beichel R., Kalpathy-Cramer, J., Finet, J., Fillion-Robin, J.C., Pujol, S., Bauer, C., Jennings, D., Fennessy, F., Sonka, M., Buatti, J., Aylward, S., V. Miller, J., Pieper, S., Kikinis, R. (2012). 3D Slicer as an image computing platform for the Quantitative Imaging Network. *Magnetic Resonance Imaging*, **2012**; 30(9); 1323-1341.
3. Isensee, F., Schell, M., Tursunova, I., Brugnara, G., Bonekamp, D., Neuberger, U., Wick, A., Schlemmer, H. P., Heiland, S., Wick, W., Bendszus, M., Maier-Hein, K. H., & Kickingereder, P. Automated brain extraction of multi-sequence MRI using artificial neural networks. *Human Brain Mapping*, **2019**; 40(17); 4952-4964.
4. Argüello, D., Sánchez Acevedo H.G. and González-Estrada. O.A. Comparison of segmentation tools for structural analysis of bone tissues by finite elements. *Journal of Physics: Conference Series*, **2019**; 1386; 012113.
5. Hyka, D., & Hyka, N. Artificial neural networks application in medical images. *International Journal of Health Sciences*, **2022**; 6(S2), 10632–10639.
6. Zou, J., Han, Y., & So, S.-S. Overview of artificial neural networks. In *Methods in Molecular Biology (Clifton, N.J.)*, **2009**; 458; 14–22.
7. Kikinis, R., Pieper, S.D., Vosburgh, K.G. (2014). 3D Slicer: A Platform for Subject-Specific Image Analysis, Visualization, and Clinical Support. In: Jolesz, F. (eds) *Intraoperative Imaging and Image-Guided Therapy*. p. 277-289. Springer, New York, NY.

8. Wang, Y., Wang, H., Shen, K., Chang, J., & Cui, J. (2020). Brain CT image segmentation based on 3D slicer. *Journal of Complexity in Health Sciences* 2020; 3(1), 34–42.
9. Yousef, R., Gupta, G., Yousef, N., et al. A holistic overview of deep learning approach in medical imaging. *Multimedia Systems*, 2022; 28; 881–914.
10. Hyka, D., & Hyka, N. Developing numerical methods and simulations for trainings in radiotherapy. *Science & Technologies, Nautical and Environmental Studies*, 2018; 8(2); 25-30.
11. Hyka, N., & Khako, D. New method to calculate the tumor control probability for PPIR. *AIP Conference Proceedings* 2019; 2178; 030052.
12. AI4MED. (n.d.). Available online: <https://ai4med.net> (accessed on 20 December 2024).
13. PyTorch. (n.d.). Available online: <https://pytorch.org/> (accessed on 20 December 2024).
14. Yip, S. S. F., Parmar, C., Blezek, D., Estepar, R.S.J., Pieper, S., Kim, J., Hugo J. W. L. Aerts. Application of the 3D Slicer chest imaging platform segmentation algorithm for large lung nodule delineation. *PLoS ONE* 2017; 12(6), e0178944.
15. M. Fu, H. Yan, C. Zhou, L. Wang, H. Ma and Z. He, "SegExtension: A Lightweight Segmentation Extension Based on 3D Slicer," 2024 7th International Conference on Computer Information Science and Application Technology (CISAT), Hangzhou, China, 2024, pp. 1391-1397,
16. Vasilev Y.A., Savkina E.F., Vladzimirskyy A.V., Omelyanskaya O.V., Arzamasov K.M. Overview of modern digital diagnostic image markup tools. *Kazan Medical Journal* 2023; 104(5); 750-760.
17. Vaz, T. F., Canto Moreira, N., Hellström-Westas, L., Naseh, N., Matela, N., & Ferreira, H. A. Brain Extraction Methods in Neonatal Brain MRI and Their Effects on Intracranial Volumes. *Applied Sciences*, 2024; 14(4); 1339.
18. Al-Garni, A., Aslam, S., Assis, Z., et al. Proceedings of the 15th International Newborn Brain Conference: Neuro-imaging studies: Fota Island, Cork, Ireland, 28 February – 2 March 2024. *Journal of Neonatal-Perinatal Medicine*, 2024; 17(3); S421-S445.
19. Hou, X., Yang, D., Li, D., Liu, M., Zhou, Y., Shi, M. A new simple brain segmentation method for extracerebral intracranial tumors. *PLoS ONE* 2020; 15(4); e0230754.
20. Safdar, S., Barry, N., Bynevelt, M., Gill, S., Farzad, P.R., & Ebert, M.A. SlicerBatchBrainMRTumorSegmentation: Automating brain tumor segmentation in 3D slicer for improved efficiency and research support. *SoftwareX*, 2024; 28; 101966.
21. Zhang, X., Zhang, K., Pan, Q., & Chang, J. Three-dimensional reconstruction of medical images based on 3D slicer. *Journal of Complexity in Health Sciences*, 2019; 2(1); 1-12.
22. Weber, J. L. (2022). *3D Slicer as a platform for the automatic segmentation of real-time MRI data* (Doctoral dissertation, Technische Hochschule Köln).
23. Uday, P. A., Digvijay, N., & Jeeva, J. B. (2014, March). Pre-operative brain tumor segmentation using SLICER-3D. In *2014 international Conference on green computing communication and electrical engineering (ICGCCEE)* (pp. 1-4). IEEE.
24. Guerrouddji, M. A., Amara, K., Benbelkacem, S., Oulefki, A., Zenati, N., Aouam, D., ... & Masmoudi, M. (2021, November). Automatic brain tumour segmentation, and 3d reconstruction and visualization using augmented reality. In *2021 International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP)* (pp. 1-5). IEEE.
25. Bashir, H., Hussain, F., & Yousaf, M.H. Smart algorithm for 3D reconstruction and segmentation of brain tumour from MRIs using slice selection mechanism. *SmartCR*, 2015; 5(3); 187-200.

26. Helms, G. Segmentation of human brain using structural MRI. *Magnetic Resonance Materials in Physics, Biology and Medicine*, **2016**; 29(2); 111-124.
27. Liu, J., & Wang, B. Application of 3D-Slicer Software in the Treatment of Gliomas. *Journal of Craniofacial Surgery*, **2024**; 39527709.