Comparative Analysis of Real-Clinical MRI and BraTS Datasets for Brain Tumor Segmentation

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Abstract

This study compares the BraTS 2020 dataset with a Real-Clinical dataset from Ankara Bilkent City Hospital for brain tumor segmentation. We analyzed histogram attributes and image dimensions, revealing that the Real-Clinical dataset has a more diverse and skewed intensity distribution compared to the uniformity of the BraTS dataset. This inconsistency suggests potential challenges for algorithms trained on BraTS data when applied in clinical settings, which exhibit greater image variation. Additionally, the higher resolution and inclusion of the entire skull in the clinical dataset complicate processing and segmentation, necessitating more robust algorithms. Our research underscores the importance of developing advanced machine-learning tools that can handle the complexity and variability of clinical MRI scans, enhancing diagnostic accuracy and clinical applicability. This study lays the groundwork for improving medical imaging algorithms to ensure their effectiveness in real-world clinical environments.

Keywords: Medical Image Analysis, Brain Tumors, Skull-Stripping, Neuroimaging, Brain Cancer Diagnosis

1 Introduction

Accurate recognition and segmentation of brain tumors are critical to their effective diagnosis and treatment; this is a procedure that is greatly facilitated by developments in automated machine learning techniques. By utilizing advanced algorithms to analyze intricate medical images, these technologies improve the accuracy and efficiency of tumor detection and segmentation. This ability is critical not solely for diagnosis, but also for the development of targeted therapies, the tracking of disease advancement, and the undertaking of research that may open the way for innovations in oncological treatment approaches (Bagherian Kasgari et al., 2023; Bakhshi et al., 2024; Balaha & Hassan, 2023; Ranjbarzadeh et al., 2023).

Magnetic Resonance Imaging (MRI) plays a critical role in this domain, functioning as a fundamental tool for the non-invasive analysis of brain structures. Brain tumor identification and characterization require high-resolution images provided by MRI, which offer in-depth information regarding the size, location, and potential infiltration of the tumor into neighboring tissues. However, the efficacy of automated segmentation is significantly influenced by several variables, such as the resolution and quality of the MRI scans as well as the effectiveness of preprocessing methods such as skull-stripping. For optimal segmentation results, it is critical to utilize high-quality, high-resolution images. Additionally, to direct the algorithm's analysis toward the brain tissue itself, it is vital to

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perform efficient skull-stripping to eliminate extraneous anatomical features (Chen et al., 2024). Keleş et al. further demonstrated that the decision-making process of the proposed machine learning model for brain tumor classification is impacted by regions associated with skull bones, thereby diminishing the model's attention to the tumor region (Keles et al., 2023). The accuracy of machine learning algorithms in segmenting brain tumors is influenced by these elements collectively. This emphasizes the significance of optimizing image acquisition and preprocessing to enhance diagnostic and therapeutic results.

2 Material and Method

2.1 Dataset Description

2.1.1 BraTS Dataset

The BraTS dataset, also known as the Brain Tumor Segmentation dataset, is widely recognized in the field of medical imaging. It is primarily used for the creation and testing of algorithms that can accurately identify and segment brain tumors. The data is accessible to the public and has played a crucial role in the annual Multimodal Brain Tumor Segmentation Challenge, which takes place at the MICCAI conference and other similar events. To obtain access to the dataset, researchers are required to register and consent to specified usage terms that guarantee the ethical use of the data for scientific and educational objectives (Bakas et al., 2017, 2018; Menze et al., 2015).

This dataset consists of pre-operative MRI images from multiple institutions, which include four conventional MRI modalities: T1-weighted, T1-weighted post-contrast (T1c), T2-weighted, and FLAIR (Fluid Attenuated Inversion Recovery). The scans in the BraTS collection originate from individuals diagnosed with either high-grade glioma (HGG) or low-grade glioma (LGG) (See Fig.1). These scans are annotated to identify the tumor core, enhancing tumor, and peritumoral Edema. To enable the comparison and consolidation of data from various investigations, all MRI scans are aligned to a standardized anatomical template and undergo normalization of intensity values.

The BraTS dataset has a consistent resolution of 240×240 pixels for its images, with a uniform slice thickness throughout the dataset. Roughly 155 slices are included in each volume, providing extensive coverage of the brain and its accompanying pathological characteristics. Before being distributed, the images go through preprocessing procedures such as skull stripping and bias field correction, which enable researchers to directly utilize the data for segmentation tasks (Z. Liu et al., 2022; Mohammed et al., 2021; Ranjbarzadeh et al., 2023).

The clinical significance of the BraTS dataset is immense. It has been specifically designed to advance research in the accurate detection of brain tumors, a critical aspect in improving the diagnosis and treatment planning in neuro-oncology. The dataset exhibits both excellent imaging quality and significant patient-to-patient variability in tumor dimensions, position, and form. The presence of diversity is essential as it serves to evaluate and enhance the resilience of segmentation algorithms created by the research community.

2.1.2 Real-Clinical Dataset

The actual Real-Clinical dataset consists of MRI scans from an additional 99 individuals, obtained from Ankara Bilkent City Hospital (See Fig.1). This dataset surpasses typical academic datasets by encompassing a comprehensive range of brain imaging in real-world clinical settings, accurately representing regular medical procedures. The Ankara Yildirim Beyazit University Ethical Committee approved consent for the use of these scans, exclusively for research purposes. This certification confirms that the dataset adheres to ethical norms and protects patient privacy, allowing it to be used for academic and research purposes.

This dataset contains a diverse range of MRI modalities, including T1, T1ce (contrast-enhanced T1), T2, and FLAIR, similar to the modalities in the BraTS dataset. Nevertheless, there are notable variations in the diversity and intricacy of the instances. Every patient's scan exhibits tumor type, stage, and anatomical variations, presenting a wider range of clinical circumstances. The presence of diverse data in data analysis adds a realistic level of complexity, resulting in a more precise representation of the variability observed in clinical settings.
The images in this collection generally have a greater resolution of 512×512 pixels and include a large number of slices, with up to 132 slices per volume. Additionally, the dataset includes complete scans of the skull rather than only certain brain regions. The incorporation of the full skull introduces further complexities for segmentation tasks, necessitating the use of efficient skull-stripping methods and the management of higher data quantities. These factors are crucial for the development of algorithms that can effectively handle practical clinical applications.
Utilizing a dataset obtained from Ankara Bilkent City Hospital increases the applicability of research to real-world clinical operations. The fluctuation in the quality of images, together with the diversity of patients, challenges the resilience and flexibility of segmentation algorithms. A dataset of this nature is essential for the development of segmentation solutions that are genuinely efficient in clinical settings, guaranteeing their adaptability to a wide range of clinical images and situations. Furthermore, the dataset has obtained ethical clearance and specific approval, indicating its readiness for immediate use in research. This will facilitate studies focused on enhancing diagnostic accuracies and treatment planning.

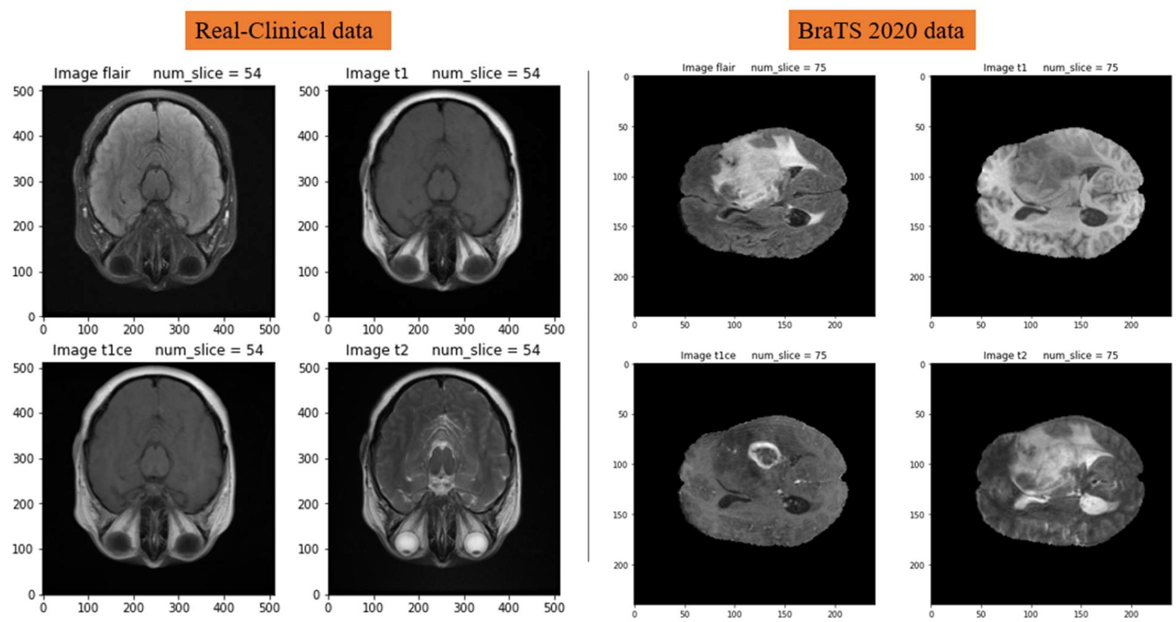

Figure 1: (Left) High-Resolution MRI scan obtained from Real-Clinical dataset provides a detailed image of the entire skull and brain. (Right) Multi-modality MRI scan from the BraTS dataset, displaying precise brain structures for a thorough tumor examination.

2.2 Annotation Process

Annotating medical images, especially in datasets such as BraTS used for brain tumor segmentation, is a crucial factor that greatly impacts the usefulness and efficiency of the dataset for training and assessing machine learning models. Annotations in medical imaging datasets act as the "ground truth" or reference standard by which

algorithms are trained and assessed. Precise annotations are essential in brain tumor segmentation since they directly influence the model's capacity to accurately detect and outline different tumor locations. Annotations assist in differentiating between various tissue types and disease characteristics, which are crucial for accurate diagnosis and therapy strategizing (Kumar Sahoo et al., 2023; H. Liu et al., 2024; Usman Akbar et al., 2024).
In the BraTS dataset, the annotation procedure requires the precise delineation of various crucial regions within the tumor:

- Whole Tumor: This annotation comprises all discernible tumor tissues observed on MRI scans, spanning all sub-regions of the tumor. It is commonly observable on T2-weighted and FLAIR images.
- Tumor Core: Mostly apparent in T1-weighted post-contrast images, this represents the majority of the tumor minus any Edema. The core typically consists of necrotic regions of the tumor, a non-enhancing solid core, and an enhancing tumor.
- Enhancing Tumor: This specific area within the tumor core exhibits increased brightness in T1-weighted post-contrast images, indicating the presence of actively growing tumor cells and malignancy.

Typically, proficient radiologists carry out these annotations, which require a significant amount of time and effort. However, they are essential for guaranteeing data of superior quality. The professionals utilize their extensive understanding of neuroanatomy and clinical characteristics of brain tumors to precisely outline every area manually. This procedure frequently entails several iterations of annotation and evaluation to minimize inaccuracies and guarantee uniformity throughout the dataset.
The process of annotating is not without difficulties. Divergence in professional judgment can result in disparities in how various annotators may interpret identical scans. Furthermore, the intrinsic intricacy of tumor structure and the level of detail in MRI scans can impact the precision of annotation. For example, annotating tiny or diffusely infiltrating tumors can be particularly difficult to do accurately. Further, annotating medical images presents difficulties when healthcare workers are unfamiliar with the labelling software. However, due to the demanding schedules and lengthy surgeries of healthcare professionals, finding time for pre-training is challenging and costly. Additionally, the requirement for certain knowledge and skills makes the process of annotating extensive datasets demanding in terms of resources. This requirement can impede the pace at which fresh datasets are generated and disseminated to the scientific community.

2.3 Skull-Stripping Challenge

The removal of non-brain tissues from MRI scans, including the skull, scalp, and dura mater, is an essential preprocessing stage in brain tumor segmentation. This process ensures that the brain is isolated for deeper analysis. The variability of anatomical structures among patients and the similar intensity values shared by brain tissues and non-brain components (e.g., the skull and scalp) in MRI images present obstacles to this procedure. The efficacy of skull-stripping greatly influences the accuracy of subsequent segmentation. Any remaining non-brain tissue remnants may introduce inaccuracies that compromise the delineation and quantification of tumors (Chen et al., 2024). The challenge is comparatively less severe in datasets such as the BraTS, where images are frequently preprocessed, unlike real-clinical datasets that may contain a full skull. The latter requires the development of robust and adaptable skull-stripping methods capable of processing a greater variety of images.
Real-world clinical settings, such as the dataset obtained from Ankara Bilkent City Hospital, present further complexities in the process of skull-stripping when complete skull scans are included. The comprehensive and high-resolution representation of the skull requires the adoption of complex techniques capable of precisely differentiating minute variations in tissue densities and boundaries. Conventional skull-stripping methods, while they may exhibit satisfactory performance on curated datasets such as BraTS, frequently struggle to handle the

heightened intricacy and variability of real-world situations. Furthermore, the task is further complicated by the existence of pathology, including tumors that have the potential to alter the structure of the brain normally or manifest close to bone-like formations. To tackle these concerns, there is a growing trend of utilizing sophisticated machine learning structures, specifically those that incorporate deep learning, to enhance the reliability and precision of skull-stripping in various clinical settings (Hoopes et al., 2022; Pei et al., 2022). This ultimately improves the overall utility of MRI data to segment and analyze tumors with extreme accuracy.

3 Results and Discussion

Although both datasets contain high-resolution MRI scans, the resolution and number of slices differ significantly. The BraTS dataset comprises 155 slices per volume and generally comprises images with a resolution of 240×240 pixels per slice. This detailed and consistent dataset establishes a solid foundation for segmentation in numerous research investigations. On the other hand, the Real-Clinical dataset comprises scans that exhibit a reduced number of slices per volume (132) but a higher resolution of 512×512 pixels per slice. While the Real-Clinical dataset possesses a superior per-slice resolution, potentially enabling more intricate visualization of smaller anatomical structures, the incorporation of the complete skull introduces processing and segmentation complexities as a result of the additional anatomical features.

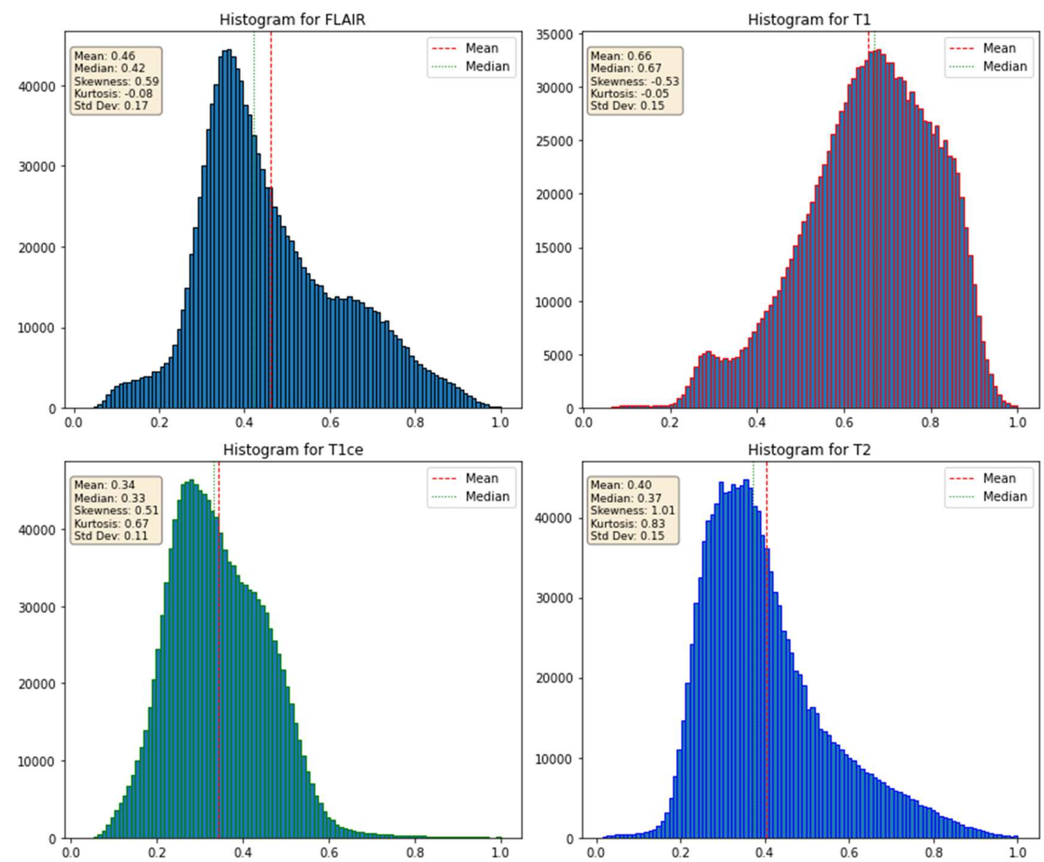

Figure 2: Histogram of a Sample MRI Scan from the BraTS 2020 Dataset.

The tumor segmentation process is influenced by intrinsic differences in image characteristics, as evidenced by the histogram and dimensional analyses. Although the consistent intensity distribution in BraTS simplifies the segmentation process, the Real-Clinical dataset's increased resolution and structural complexity necessitate the use of robust and adaptive segmentation algorithms.

The results of analyzing two samples from both datasets using histograms are indicated in Figs. 2 and 3. To isolate the tissue pattern exclusively, zero-value pixels (background) were eliminated during the analysis of the histograms of two sample MRI scans—one from the BraTS 2020 dataset and the other from the Real-Clinical dataset. The histogram for the BraTS 2020 sample has a mean intensity of 0.46, a median intensity of 0.42, skewness of 0.59, a small negative kurtosis of -0.08, and a standard deviation of 0.14. A moderate level of intensity is indicated by this profile's comparatively symmetrical distribution. With a higher skewness of 1.22, positive kurtosis of 0.54, and a standard deviation of 0.2, the real clinical sample demonstrates a significantly lower mean intensity of 0.2 and median of 0.07. The metrics suggest that the distribution is skewed, exhibiting greater variability and a rise of a heavier tail towards greater intensities.

The results underscore the need for the development of segmentation algorithms that possess the ability to adapt and effectively handle the wide range of intensities and structural intricacies present in Real-Clinical data from the real world. Improving the capability of algorithms to process standardized research datasets and high-resolution clinical images is essential for enhancing diagnostic precision and clinical utility.

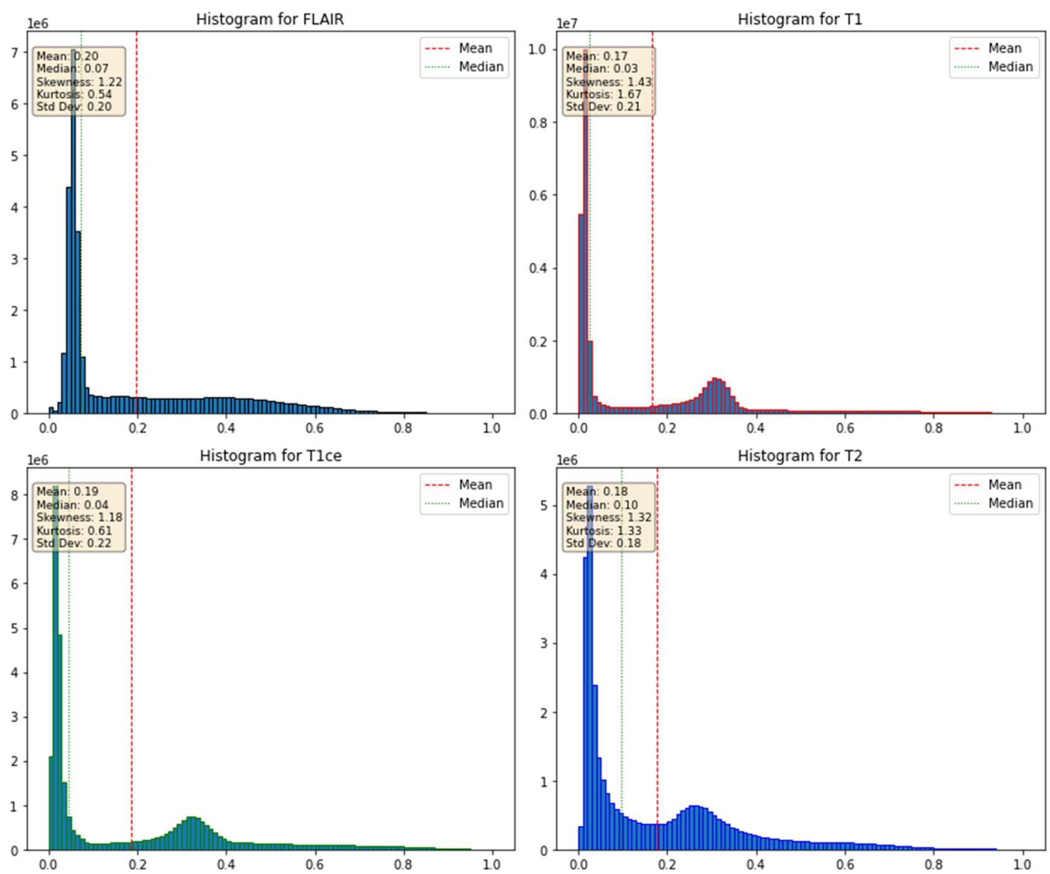

Figure 3: Histogram of a Sample MRI Scan from the Real-Clinical Dataset at Ankara Bilkent City Hospital.

4 Conclusions

A comprehensive comparison was conducted in this study between the meticulously curated BraTS 2020 dataset and a Real-Clinical dataset consisting of MRI scans obtained from Ankara Bilkent City Hospital. The analysis centered on histogram evaluation, image dimensions, and the efficiency of skull-stripping. The results of our study draw attention to notable variations in intensity distributions and image attributes, thereby emphasizing the difficulties and importance of creating resilient segmentation algorithms for brain tumors.

The examination of the histogram indicated that the intensity distribution of the Real-Clinical dataset is more diverse and skewed in nature, in contrast to the BraTS dataset which displays a more uniform distribution. This suggests that although algorithms built on BraTS may exhibit satisfactory performance in controlled environments, they might encounter difficulties when confronted with the fluctuations and uncertainties inherent in clinical settings. While the enhanced resolution of the Real-Clinical dataset provides benefits such as the ability to visualize intricate anatomical details, it also presents further computational difficulties and intricacies, particularly considering the scans encompass the entire skull.

In summary, this research underscores the importance of ongoing progress in machine learning approaches in order to address the disparity between academic datasets and clinical data in the real world. Furthermore, it emphasizes the significance of developing segmentation algorithms that are versatile, effective, and resilient enough to navigate the complexities and fluctuations that are intrinsic to clinical MRI scans. Further research should be dedicated to improving the adaptability and precision of algorithms, so that these computational tools can be consistently utilized in various clinical environments to assist in the accurate diagnosis and development of treatment strategies for patients afflicted with brain tumors.

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