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A Comprehensive Review of Brain Tumor Segmentation Methods: Traditional Approaches, Deep Learning, and Hybrid Model

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Abstract- Brain tumor segmentation plays a vital role in medical imaging by enabling accurate diagnosis, treatment planning, and monitoring of disease progression. Over the years, researchers have developed a wide range of segmentation techniques, each with its strengths and limitations. Traditional methods, such as thresholding, edge detection, and region-based techniques, offered simplicity and efficiency but often struggled with noise, variability, and ill-defined tumor boundaries. Statistical and model-based approaches, including clustering and deformable models, provided improved adaptability but required careful parameter tuning and high computational effort. The advent of machine learning, and more recently deep learning, particularly Convolutional Neural Networks (CNNs) and U-Net variants, has revolutionized segmentation, delivering unprecedented accuracy and robustness across diverse datasets. Hybrid approaches that integrate classical and deep learning methods are emerging as powerful solutions, balancing precision, efficiency, and generalizability. This review synthesizes these advancements, highlighting their evolution, comparative performance, and potential future directions.

Keywords: Brain Tumor Segmentation, MRI, Deep Learning, Convolutional Neural Networks, Hybrid Models, Medical Imaging.

I. INTRODUCTION

Brain tumors represent one of the most difficult challenges in modern medicine, reflecting the extraordinary complexity and fragility of the human brain. Detecting, segmenting, and treating these tumors is not only crucial for advancing medical research but also essential for safeguarding the lives and well-being of patients. Magnetic Resonance Imaging (MRI) has long been the cornerstone of this process, offering detailed views of brain structure and abnormalities. Yet, despite major advances in MRI technology, there remains a pressing need to improve the speed and precision of tumor detection and segmentation, given the diverse and often unpredictable nature of brain tumors.

This is where Machine Learning (ML), a branch of artificial intelligence, has transformed the field. By learning from large volumes of data and improving through experience, ML algorithms can analyze complex MRI scans, recognize subtle patterns, and even predict outcomes—capabilities that traditional rule-based methods often struggle to achieve. The shift from heuristic to data-driven approaches has marked a turning point in brain tumor diagnostics, setting new standards for accuracy and reliability. Figure 1 illustrates a brain tumor and its segmentation.

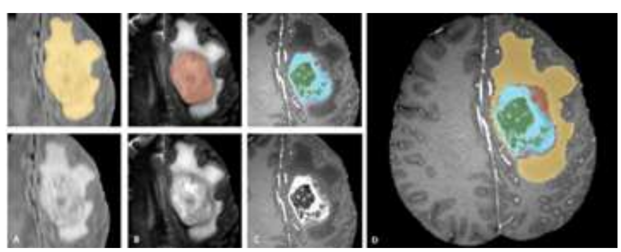

Figure 1. Brain tumor and segmentation.

Like any major technological advance, the integration of MRI imaging with machine learning brings both opportunities and challenges. Issues such as data quality, algorithmic transparency, model validation, and clinical applicability all play a critical role in determining how successful these methods can be.

This review sets out to examine this intersection of machine learning and MRI in brain tumor detection and segmentation. It traces the historical development of these approaches, evaluates the strengths and limitations of machine-learning-based methods, and considers possible future directions. By drawing on findings from a wide range of studies, the review aims to provide a comprehensive picture of the current landscape and the road ahead in applying machine learning to MRI-based brain tumor analysis.

Early efforts in the 2000s to automate MRI analysis relied largely on rule-based algorithms. While these methods were innovative for their time, they lacked flexibility and struggled with the variability of tumor characteristics. The late 2010s, however, marked a turning point with the rapid rise of machine learning—particularly deep learning and neural networks. Designed to mimic the architecture and functioning of the human brain, neural networks brought greater adaptability and learning capacity. Among them, Convolutional Neural Networks (CNNs) emerged as a cornerstone for image recognition, establishing themselves as powerful tools for medical imaging. Figure 2 illustrates brain tumor detection and segmentation in MR images.

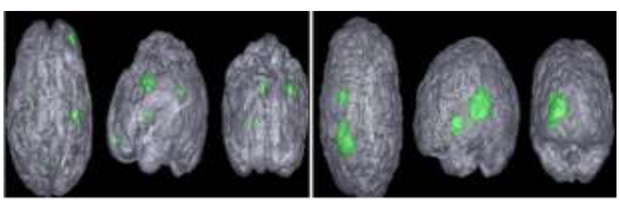

Figure 2. Brain tumor detection and segmentation in MR images.

Diving Deeper into the Realm of Brain Imaging: The human brain, often described as the most intricate organ of the body, continues to fascinate medical professionals—not only for its complexity but also for the formidable challenges it presents when afflicted with conditions such as tumors. Brain tumors, particularly malignant ones, can grow rapidly, leading to severe neurological impairments, cognitive decline, and even death if not diagnosed and treated in time.

MRI: A Revolution in Imaging: Magnetic Resonance Imaging (MRI) has emerged as a cornerstone of neuroimaging since its introduction. Unlike traditional X-rays or CT scans, MRI uses strong magnetic fields and radio waves to produce highly detailed images of the brain. These images, composed of multiple slices with varying contrasts, allow clinicians to examine both healthy and diseased tissue with remarkable precision. MRI has been especially invaluable for assessing soft tissues, providing an unparalleled view of brain structure and revealing abnormalities that might otherwise go unnoticed.

The Machine Learning Epoch: The rapid rise in computational power and data availability has ushered in a new era dominated by Machine Learning (ML). MRI generates enormous amounts of data, and manual interpretation can be both time-consuming and prone to human error. ML algorithms, trained on large datasets, have shown exceptional ability to automate the detection and segmentation of abnormalities, speeding up diagnosis and enhancing accuracy. Techniques range from classical machine learning models like Support Vector Machines (SVMs) to more advanced deep learning architectures, particularly Convolutional Neural Networks (CNNs), which excel at image analysis tasks.

The Merger: MRI and Machine Learning: The convergence of MRI and ML represents a groundbreaking shift in medical imaging. When supplied with high-resolution MRI scans, ML algorithms can identify subtle patterns and anomalies that may elude the human eye. This integration not only streamlines the diagnostic process but also opens the door to personalized treatment strategies, offering patient-specific insights that enhance clinical decision-making.

Challenges and the Road Ahead: Despite these advances, several challenges persist. Integrating ML seamlessly into clinical workflows, ensuring data privacy, and addressing the variability of MRI data across institutions remain major hurdles. Moreover, interpretability remains a pressing concern: in medicine, understanding why an algorithm makes a particular prediction is often as critical as the prediction itself. Building trust among healthcare professionals depends on resolving these issues.

Current Landscape: Today, the field of ML-based brain tumor detection and segmentation is dynamic and rapidly evolving. Advances in computational capabilities and algorithmic design are pushing the boundaries of accuracy and efficiency. Approaches such as transfer learning—where pre-trained models are adapted for medical imaging—are helping overcome the challenge of limited datasets, which often arise due to strict privacy concerns. Still, concerns remain: biased or low-quality training data can compromise outcomes, and the lack of transparency in decision-making can hinder clinical adoption.

The Path Ahead: Looking forward, this review will explore the machine learning models that are making a significant impact on MRI-based brain tumor detection. We will evaluate their strengths, assess their limitations, and highlight emerging innovations. The journey underscores not only the remarkable technological progress but also the essential collaboration among radiologists, data scientists, and engineers—all working together to unlock the potential of machine learning and, ultimately, improve patient care.

II. LITERATURE REVIEW

Monitoring Metastatic Brain Diseases

Monitoring metastatic brain diseases is particularly challenging, especially when multiple metastases are present. The RANO-BM guideline remains widely used for therapy response assessment, but accurate volumetric evaluation of lesions and peri-lesional edema is equally crucial. Brain metastases are often smaller than 10 mm, which makes segmentation difficult. Unlike gliomas, which usually present as larger masses, metastases vary widely in size and morphology. To address these complexities, the BraTSMETS dataset was introduced to facilitate advancements in automated detection and segmentation of brain metastases [1].

Advances in Brain Tumor Segmentation

Brain tumor segmentation continues to play a pivotal role in medical imaging. Despite its complexity, deep learning approaches have shown remarkable success in this domain. A comprehensive survey of more than 150 papers on deep learning–based segmentation highlights innovations in network design, methods for handling imbalanced data, and multi-modality integration. The survey also points to promising directions for future research [2].

Deep Learning Models for MRI-Based Detection

MRI remains the gold standard for early-stage brain tumor detection. However, tumor variability makes detection challenging. To overcome this, researchers proposed an Improved Invasive Bat (IIB)-based Deep Residual Network model, demonstrating strong results with high accuracy, sensitivity, and specificity [3].

When different segmentation techniques were applied to the BRATS-2018 dataset, methods such as Otsu's thresholding, watershed, level set, K-means clustering, discrete wavelet transform (DWT), and convolutional neural networks (CNNs) were compared. Among them, CNN-based approaches achieved the highest accuracy and fastest response times, reaffirming their dominance in tumor imaging tasks [4].

Hybrid and Optimized Approaches

More advanced models have pushed performance boundaries even further. A hybrid Deep Convolutional Neural Network (DCNN) classifier, enhanced with a LuNet algorithm and Laplacian of Gaussian (LOG) filter for feature extraction, achieved 99.7% accuracy, significantly improving over traditional classifiers [5].

Similarly, an optimized eXtreme Gradient Boosting (XGBoost) model has been proposed for brain tumor identification, yielding high accuracy and precision. This approach highlights the potential of ensemble learning methods in medical imaging [6].

Another study focused on segmentation across multiple brain diseases using data from Harvard Medical School, where a deep learning–based method delivered strong accuracy and sensitivity, further supporting its clinical utility [7].

CNN Architectures in Practice
The VGG16 model, trained on MRI images from Kaggle, classified cases as either "normal" or "tumor" with an accuracy of 97.33%. While effective, VGG16 is often criticized as a "black box" model. To improve transparency, Layer-wise Relevance Propagation (LRP) was employed, allowing insight into the decision-making process [8].

Another approach tackled the challenge of distinguishing tumors from normal tissues—an inherently difficult task due to their similar appearances. Preprocessing with a HOFilter, followed by segmentation using edge detection and morphological operations, achieved 96.46% accuracy and 96.19% precision [9].

Diagnostic Methods with Deep Learning
Accurate early-stage diagnosis remains critical for effective treatment. Studies using MRI have demonstrated reliable classification of gliomas, meningiomas, pituitary tumors, and healthy brains. Among the tested algorithms, 2D CNNs achieved 96.47% accuracy, while auto-encoder networks reached 95.63%. Traditional machine learning techniques were also compared, with K-Nearest Neighbors (KNN) delivering the highest accuracy among them [10].

Toward More Precise Brain Tumor Diagnosis
Early detection of brain tumors—whether malignant or benign—is critical because of their disruptive effects on surrounding cells. To enhance diagnostic accuracy, researchers proposed a CNN model fine-tuned with ResNet50 and U-Net, achieving strong segmentation metrics (IoU = 0.91, DSC = 0.95) [11].

Advances in Object Detection Architectures
Recent innovations in detection frameworks have also shown promise. An enhanced YOLOv7 model demonstrated reliable identification of pituitary gland, meningioma, and glioma tumors. This architecture integrated data augmentation, a CBAM attention mechanism, and a Bi-directional Feature Pyramid Network (BiFPN), yielding superior feature extraction and rapid feature fusion, making it both accurate and clinically relevant [12].

Hybrid and Novel Deep Learning Models
Efforts to refine segmentation further led to the design of a convolution-based hybrid model, which achieved Dice scores of up to 93.10% across multiple datasets, thanks to its unique preprocessing structure [13]. Complementary reviews emphasize the central role of CNNs in MRI-based segmentation, highlighting how deep learning has driven many of the recent breakthroughs [14].

Multi-Modal and Feature-Based Enhancements
The integration of U-Net with 3D CNNs, enhanced by Gray Level Co-occurrence Matrix (GLCM) features, demonstrated accuracies of up to 99.4% in aggressive glioma segmentation [15]. However, a key barrier remains: preprocessing steps such as skull-stripping. Studies show that the choice of brain extraction method can affect performance by up to 15.7%. Interestingly, training directly on raw images without skull-stripping reduced processing time without compromising accuracy, pointing toward more streamlined pipelines [16].

Classical Machine Learning with Deep Learning Synergy
Deep learning continues to dominate, but classical ML techniques retain value when used strategically. For example, ANN and MLP architectures were used with preprocessed MRI features to achieve reliable tumor detection [17]. Meanwhile, WBM-DLNets, which tested 16 pretrained networks and 8 optimization algorithms, revealed that combinations like DenseNet-201 with GWOA and EfficientNet-b0 with ASOA achieved the highest classification accuracy [18].

Emerging Segmentation Techniques
Hybrid frameworks are also gaining traction. A novel method combining AMSOM and FKM improved segmentation efficiency, outperforming existing models on the BraTS-18 dataset with a 10% performance gain [19]. Broader reviews underscore the diversity of approaches—ranging from computational intelligence to advanced CNNs—and

their utility in dissecting the morphological complexity of brain tumors [20].

Next-Generation Architectures
Improved Residual Networks (ResNet variants) have been shown to outperform traditional models, delivering around a 10% boost in performance metrics [21]. CNNs remain central to diagnostic AI, with studies benchmarking them against architectures like ResNet-50 and VGG16. Results consistently show CNN superiority in tumor detection tasks [22]. Similarly, SGC-ARANet, designed with four specialized modules, achieved superior boundary segmentation when tested on BraTS 2019 and 2020 datasets [23].

Handling Missing Modalities and Resource Efficiency
Medical imaging often suffers from incomplete modality data. Addressing this, a meta-learning strategy improved performance in partial-modality scenarios, outperforming competing methods [24]. Another study proposed a harmony search algorithm–based MRI segmentation method, which matched CNN and DLA in accuracy but excelled in speed and computational efficiency—critical for resource-constrained environments [25].

Beyond Medical Imaging: Cross-Domain AI Applications
Several parallel advances in AI showcase transferable methods relevant to brain tumor detection. Examples include:

- AIIoT devices for real-time object detection for visually impaired users [26].
- Efficient Arithmetic Logic Unit (ALU) designs using QCA technology [27].
- Hierarchical clustering for social recommendations.
- Deep learning applications in mask detection [28], cancer prediction [29], and object detection with Mask-RCNN [31].

Patch-Based and Ensemble Learning Methods
In MRI-focused research, a Patch-Based Convolutional Neural Network (PBCNN) was introduced for early segmentation [32]. U-Net architectures, trained on the MICCAI BRATS 2018 dataset, also achieved strong performance in automated segmentation tasks [33]. To address small-tumor detection, techniques employing dilated convolution and level-based learning improved detection across scales [34]. Additionally, an ensemble Bagging KNN (BKNN) approach boosted classification accuracy to 97.7%, further validating hybrid strategies [35].

III. RESEARCH GAP

Use of X-rays for Brain Imaging: Traditional approaches to brain tumor detection and segmentation have relied heavily on imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. These methods provide high-resolution structural details and have become the gold standard for neuroimaging. In contrast, X-rays, though widely used in other areas of medical imaging, are rarely considered for brain tumor diagnosis due to their limited capacity to capture the brain’s intricate soft tissue structures. This creates a clear research gap, as relatively few studies have explored the potential of X-rays for tumor detection, segmentation, or even as a supplementary imaging modality. Investigating this underexplored area could open new avenues for cost-effective and accessible diagnostic tools.

Integration with Machine Learning: Machine learning (ML) has demonstrated significant promise in medical imaging, particularly in the analysis of MRI and CT scans for tumor detection and segmentation. However, its application to X-ray imaging in the context of brain tumors remains underexplored. The majority of research efforts have concentrated on modalities offering richer detail, such as MRI, leaving X-rays largely unaddressed. This represents an important gap, as leveraging ML to enhance the interpretive power of X-rays could potentially compensate for their inherent limitations in resolution and contrast, while also broadening the scope of diagnostic possibilities.

Quality of X-ray Images: One of the primary challenges associated with X-ray imaging for brain tumor detection lies in the quality of the images themselves. Unlike MRI and CT scans, X-rays provide lower-resolution images with limited soft tissue contrast, making it difficult to differentiate tumor tissue from healthy brain matter. While advanced image processing techniques exist, the specific challenges of handling low-quality X-ray brain images have not been fully addressed in the literature. This gap highlights the need for specialized preprocessing pipelines and enhancement methods that can make X-rays more clinically useful in this domain.

Diverse Algorithms for X-rays: Machine learning algorithms that have proven effective for MRI or CT imaging may not necessarily perform well on X-ray images. The inherent differences in image quality, texture, and contrast demand algorithms tailored specifically to the characteristics of X-rays. However, most existing studies employ general-purpose architectures without sufficient customization for this modality. This gap underscores the need for research focused on developing or adapting algorithms that can reliably extract meaningful features from X-ray data for brain tumor detection and classification.

Real-time Detection: X-rays are generally faster and less resource-intensive to acquire and process compared to MRI or CT scans. This positions them as a potentially valuable tool for real-time tumor detection, particularly in emergency or resource-limited settings. However, there is little research exploring the feasibility of combining X-ray imaging with machine learning for immediate diagnostic feedback. Addressing this gap could result in practical solutions that enable faster clinical decision-making while still maintaining reasonable accuracy.

Dataset Availability: A critical bottleneck for advancing X-ray-based tumor detection using machine learning lies in the scarcity of publicly available datasets. While MRI and CT datasets are relatively well-established and widely used in competitions such as BraTS, comparable datasets for brain X-rays with labeled tumor regions are nearly nonexistent. Without sufficient annotated data, it is difficult to train and validate robust machine learning models. Developing large-scale, high-quality X-ray datasets thus represents a major research opportunity in this field.

Clinical Validation: Even if machine learning models tailored for X-ray brain tumor detection are developed, their clinical utility remains uncertain without extensive validation. To date, most research efforts on brain imaging with ML have concentrated on experimental setups rather than large-scale clinical trials. This lack of validation represents a major gap in understanding the real-world applicability of such models, and addressing it would be crucial for gaining acceptance among healthcare professionals.

Interdisciplinary Collaboration: Brain tumor detection through X-ray imaging with machine learning would require strong interdisciplinary collaboration between radiologists, data scientists, and ML engineers. Radiologists bring domain expertise on X-ray interpretation, while data scientists provide the computational and algorithmic knowledge needed to process complex data. Current research, however, shows limited collaboration across these disciplines, which hampers the development of clinically meaningful solutions. Bridging this gap could ensure that proposed models are both technically sound and clinically relevant.

Patient Safety: The safety implications of repeated X-ray exposure also remain underexplored in the context of brain tumor detection. Unlike MRI, which uses non-ionizing radiation, X-rays involve ionizing radiation, raising concerns about cumulative exposure, especially for vulnerable populations. Few studies have comprehensively compared the safety trade-offs of using X-rays versus MRI or CT for repeated diagnostic imaging. Investigating this gap could help establish clearer guidelines for when and how X-ray-based methods might be used in a safe and ethical manner.

Comparative Studies: Finally, there is a lack of comparative studies evaluating the relative strengths and weaknesses of X-ray-based machine learning models against those trained on MRI and CT data. Such studies would be invaluable in determining whether X-rays can serve as a viable complementary or alternative modality for brain tumor detection. Comparative analyses could also help identify contexts where X-ray imaging is particularly advantageous, such as in low-resource settings or for preliminary screening. Addressing this gap would provide a more holistic understanding of the potential role of X-rays in neuro-oncology diagnostics.

IV. EXISTING METHODOLOGY

Thresholding and Region-Based Methods: One of the earliest and simplest strategies for brain tumor segmentation is thresholding, which relies on the intensity values of pixels in MRI scans. Since tumorous cells typically display intensity values that differ from surrounding healthy tissue, applying a threshold allows pixels beyond this value to be classified as potential tumor regions. While this method is computationally efficient and easy to implement, its effectiveness is compromised in cases where images exhibit non-uniform illumination, intensity inhomogeneity, or noise, often leading to false positives or missed regions.

To address these shortcomings, region-based methods were introduced. These approaches focus on identifying areas of the image that share common properties such as intensity or texture, and then grouping them into candidate tumor regions. Popular techniques include region growing, where segmentation starts from a seed point and expands based on similarity criteria, and region merging, where small regions are combined to form larger, coherent tumor areas. Although more robust than simple thresholding, these methods depend heavily on the accurate selection of seed points or merging criteria, making them sensitive to initial conditions.

Edge Detection Methods: Another fundamental category of segmentation techniques relies on edge detection, which identifies boundaries or transitions between regions of differing intensity. Tumors often manifest as regions with sharp contrast relative to surrounding tissues, making edges an intuitive feature for localization. Algorithms such as the Sobel, Canny, and Prewitt operators are commonly employed to highlight these boundaries. When applied to tumors with well-defined margins, edge detection methods can yield precise outlines, assisting in clear delineation. However, tumors often present with irregular, diffused, or poorly defined boundaries, where these methods struggle to perform effectively. In such cases, the reliance on gradient-based detection can lead to incomplete or fragmented contours, limiting their reliability as a standalone approach.

Statistical Methods: Statistical approaches offer a more data-driven perspective by exploiting the inherent differences in distribution between tumor and non-tumor regions. These methods often employ clustering algorithms, which group pixels or voxels based on shared features such as intensity, texture, or spatial proximity. The K-means clustering algorithm is particularly popular, segmenting the image into clusters that can then be mapped to tumor and non-tumor tissues. Statistical techniques bring sophistication beyond basic thresholding, as they can adapt to varying intensity levels and identify subtle differences. However, their success is strongly dependent on the selection of initial parameters, such as the number of clusters or centroid initialization, which can significantly affect outcomes. Poor parameter choices may result in over-segmentation, under-segmentation, or misclassification.

Model-Based Approaches: Model-based approaches attempt to represent the tumor explicitly by constructing a mathematical or geometric model of its shape and behavior. Among the most widely used are deformable models, such as active contours (snakes), which iteratively adjust their shape to fit the tumor boundary. These models are guided by internal forces (encouraging smoothness) and external forces (attracted to image features like edges or intensity changes). This makes them highly flexible and capable of capturing irregular tumor shapes. However, they come with significant limitations: they are computationally intensive, requiring iterative refinement, and are prone to getting trapped in local minima, which can lead to suboptimal boundaries. Despite these challenges, deformable models remain influential due to their ability to incorporate prior knowledge about tumor geometry into the segmentation process.

Machine Learning and Deep Learning Techniques: The rapid rise of machine learning has transformed brain tumor segmentation. Early applications employed traditional classifiers such as Support Vector Machines (SVMs) and Random Forests, which could leverage hand-crafted features to distinguish between healthy and tumor tissue. However, the true breakthrough arrived with the advent of deep learning, particularly Convolutional Neural Networks (CNNs). CNNs have the ability to learn hierarchical features directly from raw image data, eliminating the need for manual feature engineering and dramatically improving accuracy. Architectures such as U-Net and its numerous variants have become the state-of-the-art in brain tumor segmentation, excelling in their ability to combine global context with local detail through encoder-decoder designs and skip connections. These methods not only outperform traditional techniques in terms of accuracy but also demonstrate robustness across diverse datasets and modalities, marking a paradigm shift in medical image analysis.

Hybrid Methods: Recognizing that no single method is universally optimal, researchers have increasingly turned to hybrid approaches that combine complementary techniques. For instance, thresholding may be used as a preprocessing step to narrow down candidate regions, which are then refined using clustering or model-based methods. Similarly, edge detection results can be incorporated into deformable models to guide boundary evolution more accurately. In the deep learning era, hybrid methods often involve combining CNNs with classical approaches or integrating multiple architectures into an ensemble framework. The goal is to mitigate the weaknesses of one method by leveraging the strengths of another, thereby achieving higher accuracy, robustness, and generalizability. Such approaches reflect the evolving trend toward multi-strategy solutions, tailored to the complexities of real-world medical imaging.

V. CONCLUSION

Brain tumor segmentation has progressed remarkably, evolving from traditional image processing methods to advanced deep learning and hybrid frameworks. Early approaches such as thresholding, edge detection, and region-based methods provided foundational insights but were often limited by noise, poor contrast, and variability in tumor morphology. Statistical and model-based methods improved adaptability but required careful parameter tuning and were computationally demanding. The advent of deep learning, especially CNN-based architectures like U-Net, revolutionized the field by delivering superior accuracy, robustness, and automation. Hybrid models further enhanced performance by integrating the strengths of multiple techniques. Looking ahead, the integration of explainable AI, real-time processing, and large-scale clinical validation will be critical to translating these advancements into reliable clinical practice.

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