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Machine Learning and Deep Learning for Brain Tumor Diagnosis and Classification: Methodologies, Challenges, and Future Directions

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Abstract: Brain tumors constitute a heterogeneous and life-threatening group of neurological disorders in which timely and accurate diagnosis is critical to improving patient outcomes. Conventional diagnostic practices, which rely heavily on manual interpretation of medical imaging, remain constrained by inter-observer variability, subjective judgment, and limited reproducibility, particularly when assigning tumor grades according to the World Health Organization (WHO) classification system. In recent years, machine learning (ML) and deep learning (DL) have emerged as transformative computational paradigms capable of automating complex pattern recognition in neuroimaging and enhancing diagnostic precision, efficiency, and consistency. A comprehensive review of ML/DL-based approaches for brain tumor analysis is presented in this study, encompassing key methodologies developed for tumor detection, segmentation, and classification across WHO grades. Despite notable research advances, clinical adoption remains impeded by several critical challenges, including insufficient dataset size and heterogeneity, a lack of model interpretability, limited generalizability across imaging acquisition protocols, and barriers associated with clinical integration and regulatory approval. Addressing these obstacles will require the development of large-scale, standardized, and multi-institutional datasets; the advancement of explainable artificial intelligence (XAI) frameworks to enhance clinical trust; and the incorporation of multi-modal patient data to improve diagnostic robustness. Furthermore, the convergence of ML/DL with emerging technologies such as blockchain and the Internet of Things (IoT) holds promise for enabling privacy-preserving, interoperable, and real-time diagnostic platforms. With continued advancements in algorithmic robustness, interpretability, and cross-institutional validation, ML/DL-based frameworks hold the potential to revolutionize brain tumor diagnosis and classification, ultimately improving diagnostic precision, prognostic assessment, and personalized treatment planning.

Keywords: Machine learning; Deep learning; Brain tumor; Diagnosis; Classification; Medical imaging; World Health Organization classification; Artificial intelligence

1. Introduction

Malignant brain tumors represent a significant and challenging class of diseases within neurology and oncology, contributing substantially to global cancer mortality (Patel et al., 2019). Brain tumors are marked by the rapid growth of unusual cells in the skull, and they vary greatly in their positions, sizes, shapes, and biological features. This variety includes both non-cancerous and very aggressive cancerous types, with the latter often spreading into nearby brain tissue or other parts of the body, which makes diagnosis and treatment especially challenging. Early and accurate diagnosis is paramount, as it dramatically influences prognosis and treatment efficacy. For instance, the five-year survival rate for brain tumor patients can increase significantly, from approximately 14% post-surgery to over 70% when detected at an early stage (Maqsood et al., 2022). Current developments in artificial intelligence (AI) show great potential in helping to detect tumors efficiently. In the United States, more than 86,000 cases of primary brain and central nervous system tumors are recorded each year, with glioblastoma being the most common type of malignant tumor (Low et al., 2022). Meanwhile, in Africa, brain cancer treatment is still hampered by limited health infrastructure and a lack of comprehensive data (Uwishema et al., 2023).

Right now, doctors mainly use medical imaging techniques like magnetic resonance imaging (MRI) and computed tomography (CT) scans to diagnose and assess brain tumors, often adding a biopsy for a clear tissue analysis (Preetha et al., 2023). While invaluable, the manual interpretation of these images by radiologists and clinicians faces significant limitations. The natural differences in how people see things, variations between different observers, issues with image quality, and the way early tumors can look similar can cause mistakes and delays in diagnosis. Additionally, accurately identifying brain tumors based on set guidelines, like the WHO grading system (Grades I-IV), is difficult because tumors can look very different at various stages, which is important for understanding the patient's outlook and planning treatment. The difficulty in achieving consistent, rapid, and accurate manual assessment highlights a critical need for improved diagnostic tools (El-Dahshan et al., 2014).

Recently, AI, particularly ML, has emerged as a powerful paradigm with transformative potential in various fields, including medical image analysis (Rajeswari & Jagannath, 2017). ML algorithms can learn complicated patterns from data, which allows them to automate and improve the accuracy of difficult tasks for human experts, like spotting small issues or measuring complex details in medical images. Applications of ML in cancer diagnostics, including segmentation, detection, and classification of tumors, have shown promising results, demonstrating performance comparable to, or even exceeding, human capabilities in specific tasks (Kang et al., 2021). In addition, a systematic review of mammography screening shows that AI-assisted reading has diagnostic accuracy equivalent to or superior to double reading by radiologists, with the added benefits of reducing unnecessary recalls and radiologist workload (Abu & Abuabeileh, 2025).

Specifically, for brain tumors, ML techniques hold immense promise to address the limitations of manual image interpretation by providing objective, consistent, and potentially faster analysis (Naser & Deen, 2020). These methods can aid in both the detection of tumors and, more critically, their accurate classification based on characteristics predictive of their grade and behavior (Kang et al., 2021). However, despite the significant advancements and numerous proposed ML models for brain tumor analysis, several challenges remain. The performance of different ML approaches can vary widely depending on the algorithm, data quality, and specific task (e.g., detection, classification, and the grading of tumors) (Işın et al., 2016). There is a need for systematic evaluation and comparison of these techniques to understand their strengths, weaknesses, and reliability across different brain tumor characteristics and WHO grades (Işın et al., 2016). Furthermore, establishing trust and facilitating the clinical adoption of AI-based diagnostic tools require demonstrating their performance rigorously against established standards (Tucci et al., 2022).

To contribute to bridging this gap, this study presents a comprehensive analysis and comparison of various ML methodologies applied to the diagnosis and classification of brain tumors based on the WHO grading system. This research looks at how well different ML methods work on a specific dataset to help diagnose and classify brain tumors, aiming to offer useful information about automated brain tumor grading and find better ways to create accurate diagnostic tools that can aid doctors and improve patient care.

2. Background on ML and Related Work

2.1 Introduction to ML in Medical Imaging

ML, a prominent subfield of AI, empowers computational systems to learn from data, identify intricate patterns, and make data-driven decisions or predictions without being explicitly programmed for every possible scenario (Antonopoulos et al., 2020). This capability is particularly transformative in the analysis of complex datasets, such as those encountered in medical imaging. By enabling automated feature extraction and pattern recognition, ML techniques offer significant potential to augment human expertise, improve efficiency, and enhance the accuracy of diagnostic processes in healthcare (Marias, 2021).

Within the domain of medical imaging, ML algorithms are increasingly being applied to tasks such as image segmentation, anomaly detection, disease prediction, and classification. The ability of ML models, especially those based on DL, to process high-dimensional image data and learn hierarchical representations directly from raw pixels has led to breakthroughs in various medical applications, including the analysis of radiological images for cancer detection and characterization (Işın et al., 2016). Recent advances in medical technology have accelerated the development of computational medicine, supported by the availability of large-scale medical datasets, increased computing capacity, and continuously evolving algorithmic innovations. DL methods are now one of the most reliable tools for analyzing complex biomedical data without the need for extensive feature extraction (Antonopoulos et al., 2020).

2.2 Related Work on ML for Brain Tumour Classification

The application of DL for tumor analysis shows promising results in improving diagnostic accuracy and efficiency compared to manual methods (Sankararao & Khasim, 2024). Although these methods demonstrate feasibility, their performance is often limited by the quality of feature extraction and the inherent variability of tumor appearance. Researchers have developed advanced DL models specifically designed to address the complexity of brain tumor images, achieving advancements in segmentation accuracy, tumor subtype classification, and patient outcome prediction (Kaifi, 2023). These automated approaches aim to improve early detection, treatment planning, and overall patient care by providing faster and more accurate analysis of brain tumor MRI scans (Ghadi & Salman, 2022).

With the advent of DL, particularly convolutional neural networks (CNNs), the field has seen significant progress. CNNs can automatically learn relevant features directly from raw image data, often leading to superior performance compared to traditional ML approaches for image-based tasks (Kamilaris & Prenafeta-Boldú, 2018). The main challenges in applying DL models to brain tumor analysis include limited datasets, inter-modality variability in MRI (T1, T2, FLAIR, and contrast), and the need for precise segmentation at blurred tumor boundaries (Musthafa et al., 2025). Recent studies have proposed advanced architectures such as Vision Transformer and CNN-attention combinations to improve multi-modal segmentation robustness (Abidin et al., 2024).

Several comprehensive reviews have summarized the use of DL techniques for brain tumor analysis. For example, Abidin et al. (2024) provided a detailed overview of DL approaches specifically for brain tumor classification, discussing key stages from data preprocessing to model construction and highlighting both successes and limitations from a radiologist's perspective. Similarly, Nadeem et al. (2020) reviewed DL applications for brain tumor research, covering segmentation, classification, and prediction, while also identifying challenges and future research directions. Nazir et al. (2021) conducted a systematic review of DL studies published between 2015 and 2020 focused on brain tumor detection and classification, analyzing the algorithms used and reported performance metrics. Liu et al. (2023) focused on DL-based brain tumor segmentation, discussing technical challenges and methodologies. These reviews collectively demonstrate the potential of DL but also point out the importance of more reliable, generalizable, and clinically validated models. Specific studies have investigated the use of ML/DL for classifying brain tumors based on the WHO grading system (Grades I-IV), which is crucial for prognosis and treatment planning (Hollon et al., 2018).

Research on low-grade tumor classification (Grade I), which often grows slowly and is benign but can still cause serious issues, has utilized various ML approaches. Abidin et al. (2024) demonstrated the potential of ML-based decision trees applied to stimulated Raman histology for rapid intraoperative diagnosis of brain tumors in children. Bechelli & Delhommelle (2022) explored ML techniques for classifying astrocytomas, a common type of glioma. ML-based radiomics analysis was applied to distinguish posterior fossa tumors in children specifically. DL models, such as U-Net-based architectures and combinations of DL with genetics, have been studied for better segmentation and diagnosis of specific Grade I tumors like craniopharyngioma. ML algorithms based on imaging features have also been explored to identify survival biomarkers in pediatric brain cancer (Tabares-Soto et al., 2020).

Studies focusing on Grade II tumors, which have an intermediate growth rate, have also used ML/DL. Recent studies have explored ML and DL approaches for tumor classification. Tabares-Soto et al. (2020) compared various ML and DL algorithms to classify several types of cancer using microarray data, achieving an accuracy of up to 94.43% with CNNs. Bechelli & Delhommelle (2022) found that DL models outperformed ML algorithms in skin cancer classification from dermoscopy images, with pre-trained models like VGG16—a 16-layer CNN architecture developed by the Visual Geometry Group at the University of Oxford—showing high accuracy. For glioma grading classification, Çinarer et al. (2020) developed a DL-based method using wavelet radiomic features, achieving an accuracy of 96.15%. This study demonstrates the effectiveness of the DL approach in tumor classification across various types of cancer, consistently outperforming traditional ML methods and achieving high accuracy levels.

Tian et al. (2020) explained that WHO Grade III tumors, including meningioma and glioma, are aggressive neoplasms with poor prognoses. For Grade III meningioma, factors associated with better outcomes include frontal location, unifocal tumor, lower Ki-67 index, and postoperative radiotherapy. Recent studies have explored DL and ML approaches for tumor classification and grading (Raza et al., 2022). CNNs have demonstrated high accuracy in classifying various types of cancer using gene expression data (Tabares-Soto et al., 2020). For glioma grading, deep neural networks combined with discrete wavelet transforms achieved 96.15% accuracy in distinguishing between Grade II and III tumors (Çinarer et al., 2020). DL algorithms have also been applied to histopathology for tumor detection, classification, and grading, with the potential to improve diagnostic accuracy and reduce the workload for pathologists (Ahmed et al., 2022). A hybrid DL model called DeepTumorNet, based on a modified GoogLeNet architecture, demonstrated superior performance in classifying glioma, meningioma, and pituitary tumors, achieving an accuracy of 99.67% (Raza et al., 2022). These studies point out the importance of DL techniques in improving tumor classification and assessment across various types of cancer.

Glioma is a primary brain tumor classified into Grades I-IV by WHO, with Grade IV (glioblastoma) being the most aggressive (Wagner et al., 2021). Recent research has explored the use of DL for glioma classification based on medical imaging. Latif et al. (2022) combined CNN for feature extraction with Support Vector Machine (SVM), achieving high accuracy in classifying glioma subtypes from MRI. In addition, Jin et al. (2020) developed a CNN system for histological classification of glioma on hematoxylin and eosin (H&E)-stained slides enhanced with molecular markers. Çinarer et al. (2020) integrated wavelet radiomic features and deep neural networks for accurate glioma grade classification. Cluceru et al. (2021) demonstrated that diffusion-weighted imaging with a three-class CNN model improved the prediction of non-invasive glioma genetic subtypes compared to methods based solely on anatomical imaging. These findings demonstrate the potential of DL to automate and improve the accuracy of glioma classification. ML techniques have shown promising results in various healthcare applications, including disease diagnosis, mortality prediction, and clinical decision support.

Studies have demonstrated high accuracy of ML algorithms such as CNNs in diagnosing conditions like lung cancer and brain tumors (Furizal et al., 2023). However, challenges remain in applying ML in clinical settings, including data quality issues, security risks, and potential biases. To address these challenges, standardized reporting of ML models, increased data availability, and systematic evaluation of various techniques across diverse datasets are recommended (Caballé-Cervigón et al., 2020). Additionally, fairness metrics and bias mitigation strategies should be consistently applied to enhance algorithmic fairness. Going forward, more comprehensive and systematic evaluation of ML techniques on varied datasets covering all WHO grades is needed to identify reliable methods for clinical applications (Naemi et al., 2021). One of the main barriers is the integration of DL into clinical radiology workflows. Recent research has successfully integrated tumor segmentation and radiomic feature extraction algorithms into the Picture Archiving and Communication System (PACS)—enabling segmentation in approximately four seconds with seamless radiologist interaction (Aboian et al., 2022).

3. Methodology

A structured narrative approach following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles was used in this study to ensure a systematic literature search. The article selection process is illustrated in a flowchart, with searches conducted on PubMed, IEEE Xplore, Scopus, and ScienceDirect for publications from 2015 to 2025 related to ML/DL in brain tumor MRI. A similar methodology was used by Nayak et al. (2024) who assessed the quality of MRI-based radiomics methods using the Radiomics Quality Score (RQS) to ensure model validity.

Table 1. Inclusion and exclusion criteria used for shortlisting articles

Parameters	Inclusion Criteria	Exclusion Criteria
Time frame	Papers published from 2010 to 2025	Papers published before 2010
Language	English (or languages with available translations)	Articles in languages without available translations
Intervention	Application of ML and DL algorithms specifically for the diagnosis of brain tumors using MRI	Studies using other imaging techniques such as CT and Positron Emission Tomography (PET) or focusing on treatment rather than diagnosis
Study design	Peer-reviewed systematic reviews, randomized controlled trials, observational studies, and case-control studies	Conference proceedings, editorials, and non-peer-reviewed articles
Imaging	MRI as the primary imaging modality	Studies using only CT, PET, or hybrid modalities
Algorithms	Studies utilizing DL, ML, and Vision Transformer methods	Rule-based or traditional statistical analysis studies
Outcomes	Studies reporting segmentation/classification metrics (e.g., accuracy and Dice coefficient)	Studies without quantitative performance metrics, animal studies or simulated data only
Population	Studies involving human participants with brain tumors (pediatric and adult populations)	Animal studies or simulated data only

Inclusion criteria included peer-reviewed studies applying ML/DL for detection, segmentation, or classification of brain tumors using MRI data. In line with Wang et al. (2024), PRISMA guidelines were applied, and preprocessing steps such as normalization, skull stripping, and consistent train/test splitting were implemented to evaluate CNN performance in meningioma segmentation. In total, over 60 studies were reviewed and classified according to WHO tumor grade. Nassar et al. (2023) emphasized the importance of documenting training parameters, transparent architecture, and multi-institutional validation in hybrid DL methods for brain tumor classification.

The methodological approach used in the survey ensures relevance, transparency, and reproducibility while providing a coherent synthesis of recent developments in ML/DL-based brain tumor diagnosis and classification. Furthermore, Table 1 presents an overview of the inclusion and exclusion criteria used in the article screening process.

4. Challenges and Limitations

Despite the significant potential of ML and DL techniques for the diagnosis and classification of brain tumors from medical images, several formidable challenges and limitations must be overcome for successful implementation in clinical practices. These challenges encompass various aspects, including data acquisition and quality, model development and validation, and integration into existing clinical workflows.

One of the main obstacles is related to data quality and quantity. Effective ML models, especially deep neural networks, require access to large, diverse, and high-quality datasets for training. However, medical image datasets for brain tumors are often limited in size due to patient privacy concerns, data sharing restrictions, and the rarity of certain tumor types or grades. Additionally, variations in imaging protocols, scanner manufacturers, field strengths, and acquisition parameters across institutions can introduce inconsistencies and biases in the data, hindering the generalization of models trained on data from a single source (Kang et al., 2021). Data annotation is another significant challenge, as accurate labeling of tumor regions and classification requires expertise from experienced radiologists or pathologists, which is a time-consuming and resource-intensive process prone to inter-observer variability. The inherent imbalance in brain tumor datasets, where aggressive or rare tumor types are far less represented than more common ones, also poses a challenge for training robust and fair models (Tasci et al., 2022). Recent research has also shown that selecting the appropriate feature extraction method, such as a combination of Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) with random forest algorithms, can achieve high accuracy (up to 99%), but its performance is highly dependent on the quality and diversity of the dataset used, making cross-institutional validation crucial (Kumar et al., 2024).

Challenges related to the model are also critical. Complex ML models, often referred to as "black boxes", can lack transparency, making it difficult for clinicians to understand why certain predictions or classifications are made (Naser & Deen, 2020). This lack of interpretability can be a major barrier to clinical adoption, as doctors need to trust and understand the basis of AI-driven diagnoses before relying on them. Ensuring the generalization and robustness of trained models is of utmost importance. Models trained on specific datasets may perform poorly when applied to data from different hospitals or using different imaging parameters, limiting their real-world applicability. Rigorous model validation and evaluation are essential, requiring appropriate metrics that go beyond simple accuracy, especially in cases of class imbalance. Metrics such as sensitivity, specificity, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are necessary, along with comprehensive error analysis, to understand where and why a model fails. The computational resources required to train and deploy complex DL models can also be substantial, imposing practical limitations on institutions with limited infrastructure. Additionally, a comprehensive review by Kumar et al. (2024) emphasizes that the heterogeneity of cross-modal imaging data (MRI, CT, and PET) requires consistent normalization and standardization strategies, thereby ensuring that models can be transferred to different clinical environments without significant performance degradation (Iftikhar et al., 2025).

Finally, challenges related to clinical integration and adoption are critical. Integrating AI-based diagnostic tools into existing clinical workflows requires significant adjustments to current medical practices and acceptance from doctors and other healthcare professionals (Naser & Deen, 2020). Building trust in AI systems among clinicians is a gradual process that requires demonstrations of reliability and performance in real-world environments. Regulatory approval and validation are also important steps before these tools can be widely used in clinical care. Additionally, long-term maintenance, monitoring, and updates of deployed ML models are essential to ensure that their accuracy and performance remain consistent over time, especially as new data becomes available or clinical standards evolve. These requirements present ongoing challenges. Approaches such as CNN-TumorNet combined with XAI techniques have been shown to improve model transparency and help clinicians understand the basis for decision-making, which could ultimately accelerate the adoption of AI in hospital settings (Rasool et al., 2025).

Addressing these multifaceted challenges requires cross-disciplinary collaboration between researchers, clinicians, data scientists, and policymakers. Overcoming these limitations is critical to realizing the full potential of ML/DL in revolutionizing brain tumor diagnosis and improving patient outcomes.

5. Future Directions

Building upon the current state of ML applications in brain tumor diagnosis and classification and acknowledging the significant challenges outlined in the previous section, several promising avenues for future research and development emerge. Addressing these directions is crucial for translating the potential of AI into widespread clinical utility and ultimately improving patient outcomes.

One critical area for future work is addressing the limitations related to data availability, quality, and diversity. Future research should explore advanced techniques for data augmentation, synthetic data generation, and transfer learning to mitigate the issue of limited dataset size, especially for rare tumor types. Furthermore, the development and adoption of secure, privacy-preserving data sharing frameworks, such as federated learning or leveraging blockchain technology, are essential to enable collaborative model training across multiple institutions without compromising patient confidentiality. Permissioned blockchain, as highlighted, offers a robust mechanism for tracking data usage and ensuring authorized access, thereby fostering trust and facilitating larger, more diverse datasets necessary for training generalizable models.

Another key direction lies in enhancing model interpretability and explainability. As ML models become more complex, providing clinicians with clear insights into why a model makes a particular prediction is vital for building trust and enabling clinical adoption. Future research should focus on developing and integrating XAI techniques tailored for medical image analysis, allowing clinicians to validate model decisions and gain confidence in AI-assisted diagnoses. Improving the generalizability and robustness of ML models across diverse patient populations, imaging protocols, and scanner types remains a significant challenge. Future studies should prioritize rigorous multi-institutional validation using external datasets to assess model performance in real-world settings. Techniques such as domain adaptation and generalization will be critical in developing models that perform consistently well regardless of the data source. The integration of multi-modal data presents another exciting future direction. Combining information from medical imaging (MRI and CT), genomic data, pathology reports, and clinical information can provide a more comprehensive understanding of the tumor and potentially lead to more accurate diagnosis, classification, and prognosis prediction. Future ML models should be designed to effectively integrate and leverage these disparate data sources.

Furthermore, exploring and adapting advanced ML architectures and techniques beyond conventional CNNs may yield further improvements. This could include investigating graph neural networks for analyzing connectivity patterns, transformer models for capturing long-range dependencies in images, or reinforcement learning for optimizing treatment planning strategies based on diagnostic information. Finally, bridging the gap between research and clinical practice requires a strong focus on clinical validation and regulatory pathways. Future work must involve prospective studies to evaluate the impact of AI tools on clinical workflows and patient outcomes. Collaboration with regulatory bodies is also necessary to establish clear guidelines for the validation and deployment of AI-powered medical devices. IoT can play a role in facilitating real-time data collection and monitoring in clinical settings, potentially enhancing the continuous evaluation and improvement of deployed ML models.

The future of ML in brain tumor diagnosis and classification is bright but contingent upon addressing current limitations through innovative approaches in data handling, model development, validation, and clinical integration. The synergistic application of advanced ML techniques with enabling technologies like blockchain and IoT holds the potential to revolutionize how brain tumors are detected, classified, and managed, ultimately leading to more personalized and effective patient care.

6. Conclusions

Brain tumors represent a complex and life-threatening class of diseases where early and accurate diagnosis is critical for improving patient prognosis and treatment outcomes. Traditional diagnostic methods, primarily based on manual interpretation of medical images, face inherent limitations in terms of subjectivity, efficiency, and the ability to consistently classify tumors according to established grading systems like the WHO classification. This study explored the significant potential of ML and DL techniques as powerful tools to overcome these limitations in the diagnosis and classification of brain tumors. The review of related work highlights numerous studies demonstrating the capability of ML/DL models to assist in tasks such as tumor detection, segmentation, and classification across various WHO grades, showcasing promising performance metrics. However, the successful translation of these research advancements into routine clinical practices is contingent upon addressing several key challenges. These include the critical need for large, diverse, and high-quality datasets, the development of interpretable and XAI models to foster clinician trust, ensuring the generalizability and robustness of models across different imaging protocols and institutions, and navigating the complexities of clinical integration and regulatory approval.

Looking ahead, future research directions must prioritize innovative solutions for secure and collaborative data sharing (e.g., federated learning and blockchain), advancements in XAI techniques, rigorous multi-institutional validation, and the effective integration of multi-modal patient data. The synergistic application of ML with enabling technologies like blockchain and IoT holds substantial promise for creating more robust, privacy-preserving, and clinically applicable diagnostic tools.

In summary, while significant progress has been made in applying ML/DL to brain tumor analysis, ongoing research and development are essential to overcome existing challenges. The continued refinement and validation of these technologies are crucial steps towards developing reliable, accurate, and interpretable AI-powered systems that can effectively support clinicians in the diagnosis and classification of brain tumors, ultimately leading to improved patient care and survival rates.

Author Contributions

Conceptualization, R.P. and S.N.F.; methodology, S.N.F; writing—original draft preparation, S.N.F.; writing—review and editing, R.P.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

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