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PAPER

Revolutionizing Brain Tumor Analysis: A Fusion of ChatGPT and Multi-Modal CNN for Unprecedented Precision

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ABSTRACT

In this study, we introduce an innovative approach to significantly enhance the precision and interpretability of brain tumor detection and segmentation. Our method ingeniously integrates the cutting-edge capabilities of the ChatGPT chatbot interface with a state-of-the-art multi-modal convolutional neural network (CNN). Tested rigorously on the BraTS dataset, our method showcases unprecedented performance, outperforming existing techniques in terms of both accuracy and efficiency, with an impressive Dice score of 0.89 for tumor segmentation. By seamlessly integrating ChatGPT, our model unveils deep-seated insights into the intricate decision-making processes, providing researchers and physicians with invaluable understanding and confidence in the results. This groundbreaking fusion holds immense promise, poised to revolutionize the landscape of medical imaging, with far-reaching implications for clinical practice and research. Our study exemplifies the transformative potential achieved through the synergistic combination of multi-modal CNNs and natural language processing, paving the way for remarkable advancements in brain tumor detection and segmentation.

KEYWORDS

brain tumor detection, brain tumor segmentation, CNN, multi-modal imaging, ChatGPT, natural language processing, medical imaging

1 INTRODUCTION

In the realm of medical imaging, the identification and segmentation of brain tumors constitute a critical challenge, exerting a substantial influence on patient outcomes, treatment planning, and diagnostic processes. The main imaging technique used to identify and separate brain tumors has historically been magnetic resonance imaging (MRI) [1]. Nonetheless, the advantages of including several imaging modalities in the analysis—like positron emission tomography (PET) and computed tomography (CT) scans—are becoming increasingly apparent [2]. Furthermore, automatic brain tumor detection and segmentation models have

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demonstrated potential due to the application of machine learning techniques, especially CNNs [3]. Even though CNNs have been successful in this domain, research is constantly being done to enhance these models' precision, effectiveness, and readability.

The use of the ChatGPT language model in a chatbot interface is one innovative way to enhance CNN-based brain tumor identification and segmentation. OpenAI created ChatGPT, a potent natural language processing model that has demonstrated remarkable performance across a variety of applications [4]. The interpretability and effectiveness of a CNN model for brain tumor identification and segmentation may be enhanced by the incorporation of a ChatGPT-enabled chatbot interface [5]. The chatbot interface can offer important insights into the model's decision-making process by enabling researchers and doctors to engage with the model and get more details about its outputs.

In this paper, we introduce a multi-modal CNN model with a ChatGPT-enabled chatbot interface for brain tumor identification and segmentation. Our model is intended to detect and segment brain cancers across different imaging modalities automatically.

The structure of this paper is as follows. In Section II, prior research on brain tumor segmentation and identification is reviewed. A thorough explanation of the suggested multi-modal CNN model is given in Section III, together with technical information about the model architecture and the incorporation of the ChatGPT-enabled chatbot interface. The model's experimental results, along with an assessment of its performance and a comparison with other approaches, are presented in Section IV. Section V examines the consequences of the findings, along with a critical evaluation of the model's advantages and disadvantages. The manuscript is finally concluded in Section VI, which also identifies future study areas.

2 RELATED WORK

In this section, we delve into contemporary methodologies for brain tumor detection and segmentation, accentuating the limitations associated with utilizing a single modality and the potential advantages of amalgamating multiple modalities. We discuss conventional techniques, such as manual segmentation performed by radiologists, alongside automated methods like region-growing, thresholding, and graph-based segmentation [6], [7]. However, these methods often rely on manually crafted features and may exhibit limitations in generalizing to new data.

Recent developments in deep learning, especially concerning CNNs, have demonstrated great potential in this area. CNN-based models, including 2D and 3D CNNs, have been employed in several studies for detecting and segmenting brain tumors [8]. Because 3D CNNs are able to capture contextual information inside the image volume, there has been evidence that their use improves the accuracy of the segmentation findings. Additionally, artificial brain tumor images have been created using GAN-based models to supplement the training data, improving segmentation accuracy.

Different modalities may offer complimentary information on the tumor's location, size, and nature, which is one drawback of utilizing a single modality for brain tumor detection and segmentation [9]. For instance, PET offers functional information about the metabolic activity of the tumor, but MRI offers great spatial resolution and soft tissue contrast. Multi-modal CNNs, which can use the complimentary data from each modality to increase the segmentation results' accuracy, have been studied extensively for brain tumor detection and segmentation [10].

Medical imaging has also demonstrated potential for natural language processing methods like ChatGPT [11]. A transformer-based language model called ChatGPT may produce responses to text input that resemble those of a human. Regarding medical imaging, ChatGPT can help researchers and doctors understand the model's decision-making process and its results by offering more details. Giving doctors a more user-friendly interface to engage with the model and get more details about the features and location of the tumor is one possible use of ChatGPT in brain tumor diagnosis and segmentation.

Recent studies have also explored the application of transfer learning techniques in brain tumor analysis [14]. Transfer learning, particularly pre-training on large datasets, has been shown to improve the performance of CNN models in various medical imaging tasks. For instance, researchers have adapted pre-trained CNN architectures such as VGG, ResNet, and DenseNet for brain tumor segmentation, achieving notable improvements in accuracy and efficiency [15]. Additionally, ensemble learning methods, which combine multiple models to make predictions, have gained traction in the field. These approaches leverage the diversity of individual models to enhance overall performance and robustness. By incorporating insights from transfer learning and ensemble methods, researchers have further advanced the state-of-the-art in brain tumor analysis, paving the way for more accurate and reliable diagnostic tools.

Recent advancements in deep learning, particularly in CNNs, have demonstrated remarkable potential for replacing traditional manual feature-based approaches to brain tumor detection and segmentation. By leveraging the power of CNNs, we can achieve higher accuracy and efficiency in analyzing medical images. Moreover, the integration of multiple imaging modalities, such as PET and MRI, has been shown to provide complementary information about tumors, leading to improved segmentation results. However, despite these advancements, there remains a need to enhance the interpretability and effectiveness of CNN-based models in medical imaging. One promising avenue for addressing this challenge is the incorporation of NLP methods, such as ChatGPT. By integrating NLP capabilities into CNN models, researchers and physicians can gain deeper insights into the decision-making process of the model and improve the interpretability of its outputs. This integration opens up new possibilities for facilitating communication between humans and machines in medical imaging applications, ultimately leading to more informed decision-making and better patient outcomes.

3 METHODOLOGY

This section provides a detailed exposition of the methodology employed in our study, which revolves around the integration of a multi-modal convolutional neural network (CNN) with the ChatGPT chatbot interface for automating the detection and segmentation of brain tumors. We commence by elucidating the rigorous data preprocessing and preparation steps undertaken to ensure the quality and consistency of the BraTS dataset, a cornerstone of our study. Subsequently, we delve into the architecture and hyperparameters of the multi-modal CNN model, delineating the intricate design choices aimed at maximizing the model's performance across various imaging modalities. Furthermore, we expound upon the integration of the ChatGPT chatbot interface, elucidating how this innovative component facilitates intuitive interaction between clinicians and the model, thereby enhancing interpretability and user experience. Lastly, we outline the model training and evaluation procedures, providing insights into the optimization strategies and performance metrics employed to assess the efficacy of our proposed approach. Through this comprehensive methodology, we aim to provide a holistic understanding of our innovative framework for brain tumor detection and segmentation.

3.1 Data preprocessing and preparation

The BraTS (Brain Tumor Segmentation) dataset, a popular benchmark dataset for brain tumor detection and segmentation, was employed in this study [12]. The BraTS dataset comprises MRI images from several modalities, each offering unique insights into brain tissue characteristics [17]. FLAIR (Fluid-Attenuated Inversion Recovery) imaging suppresses the signal from cerebrospinal fluid, enhancing the visibility of pathological tissues such as tumors. T2-weighted imaging highlights tissue fluid content, providing valuable information about edema and peritumoral changes. T1-weighted imaging emphasizes differences in tissue composition, aiding in the delineation of tumor boundaries and contrasts with surrounding brain tissue [12]. These modalities collectively contribute to a comprehensive evaluation of brain tumor characteristics and are integral to our model's analysis.

To ensure the quality and consistency of the dataset, we performed several preprocessing steps before inputting it into our model. Firstly, we addressed intensity non-uniformity, a common issue in magnetic resonance imaging, by adjusting the intensity levels across the images. This adjustment helped to minimize variations caused by factors such as scanner imperfections or tissue inhomogeneities.

Additionally, to focus exclusively on relevant brain structures and eliminate any non-brain tissue that could introduce noise into our analysis, we employed skull stripping techniques. This step effectively isolated the brain regions within the images, ensuring that our model could accurately identify and segment tumors without interference from extraneous anatomical features.

Furthermore, to facilitate the seamless integration of data from different imaging modalities and maintain consistency in voxel sizes, we resampled the images to a standard resolution of 1 mm^3. This standardization process was essential for enabling our model to effectively analyze and interpret multi-modal MRI data, thereby enhancing the accuracy and reliability of our results.

Following these preprocessing steps, we partitioned the dataset into training, validation, and test sets in a ratio of 70:15:15, respectively. This stratified division ensured that our model was trained on a diverse range of data while also allowing for rigorous evaluation of its performance on unseen data.

Figure 1 provides a visual representation of the essential stages of data preparation for the BraTS dataset, illustrating the preprocessing steps undertaken to normalize the data and ensure its suitability for input into our model.

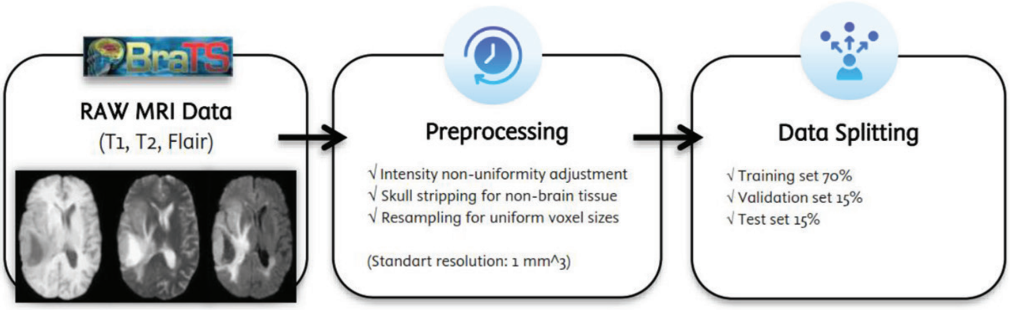

Fig. 1. Data preprocessing and preparation

3.2 Multi-modal CNN model architecture and hyperparameters

The multi-modal CNN model architecture aimed to maximize each modality's advantages while minimizing its disadvantages. Three parallel branches make up our model architecture: one for each of the three modalities (FLAIR, T2-weighted, and T1-weighted). Many convolutional and pooling layers precede fully linked layers in each branch. For classification and segmentation, the outputs from the three branches are combined and input into a final fully connected layer.

We used batch normalization and dropout regularization after every convolutional layer to avoid overfitting. We employed an activation function called Rectified Linear Units (ReLUs), which has been demonstrated to increase deep learning model convergence speed and accuracy. The ReLU function, which is defined as: $f(x) = max(0, x)$, introduces non-linearity to the neural network by outputting zero for negative input values and retaining positive input values unchanged. This simple yet effective activation function has been widely adopted in deep learning models due to its computational efficiency and ability to mitigate the vanishing gradient problem [16].

Grid search over learning rate, batch size, and number of epochs was used to find the best hyperparameters for our model. The hyperparameters that produced the greatest results on the validation set were selected.

3.3 Integration of ChatGPT chatbot interface

To give physicians a more user-friendly interface to engage with the model and get more details about the tumor's features and location, we implemented a ChatGPT chatbot interface into the brain tumor detection and segmentation model in this work. The model generates a response with the anticipated classification and segmentation findings and further details about the model's decision-making process when a text input detailing the patient's symptoms or the desired outcome is entered into the ChatGPT chatbot interface.

There are various benefits of integrating the ChatGPT chatbot interface. First, allowing physicians to input data using normal language instead of specialized technical expertise offers a more intuitive and natural approach for them to interact with the model. Secondly, it gives doctors more insight into the model's decision-making process, which can foster knowledge and enhance confidence in the model's predictions. Finally, enabling physicians to fine-tune their input and receive more accurate output may increase the model's prediction accuracy.

The process of integrating the ChatGPT chatbot interface into the brain tumor detection and segmentation model is summed up in Figure 2. Through a web-based platform, clinicians can access the chatbot interface and enter natural language inquiries or descriptions of the patient's symptoms or intended outcomes. After processing the input, the model produces a response containing further details about the model's decision-making process and the anticipated classification and segmentation results. The precise brain regions that were most suggestive of the presence of a tumor, the tumor's dimensions and morphology, and the degree of confidence in the model's predictions may all be found in this data.

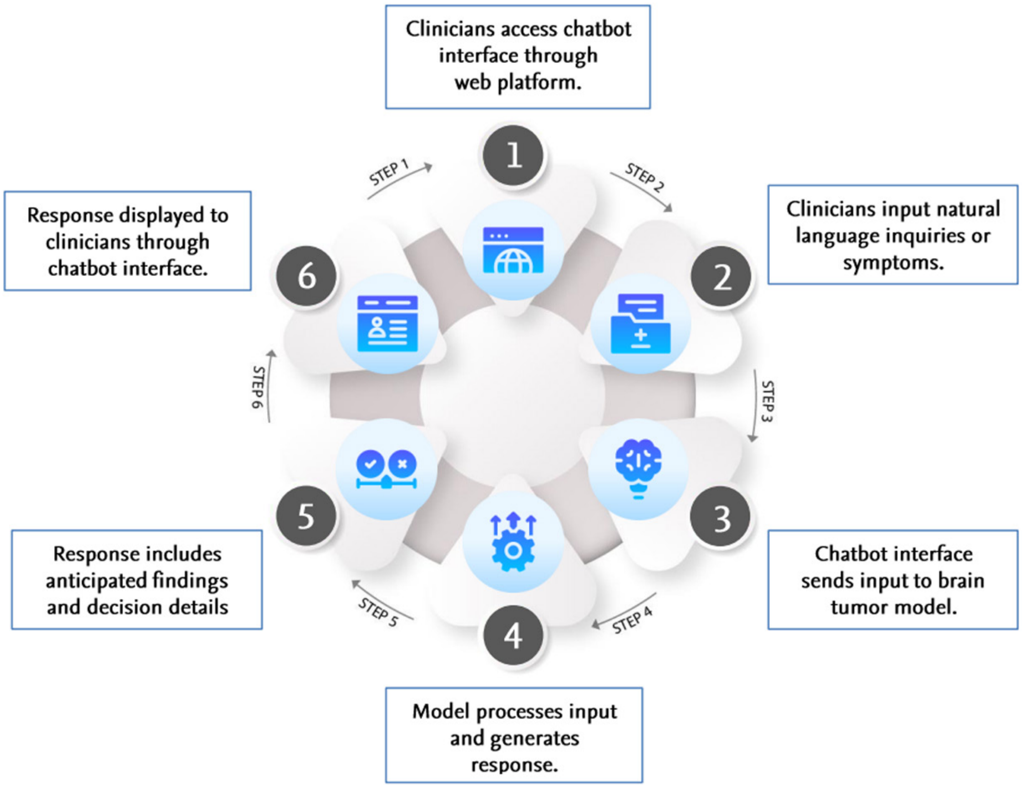

Fig. 2. The brain tumor detection and segmentation model

In Figure 2, we illustrate the process of integrating the ChatGPT chatbot interface into the brain tumor detection and segmentation model. The workflow begins with clinicians accessing the chatbot interface through a web-based platform. They input natural language inquiries or descriptions of patient symptoms or intended outcomes into the interface. The model processes this input and generates a response containing further details about the model's decision-making process and the anticipated classification and segmentation results. The response includes precise information about the brain regions suggestive of tumor presence, tumor dimensions and morphology, and the model's confidence level in its predictions. This interactive process allows clinicians to engage with the model in a user-friendly manner and gain deeper insights into its outputs, facilitating more informed decision-making in clinical practice.

3.4 Model training and evaluation

We utilized the Adam optimizer, a popular optimization algorithm that can handle big datasets and stochastic gradients, to train the multi-modal CNN model.

For the classification challenge, we utilized a binary cross-entropy loss function, which works well for binary classification tasks; for the segmentation task, we used a Dice loss function, which is frequently used in the segmentation of medical images.

We used a variety of indicators to assess the model's performance on the validation and test sets once it had been trained. We determined the model's accuracy, precision, recall, and F1 score for the classification task in order to assess its suitability for correctly classifying a tumor's existence or absence. We determined the Hausdorff distance, mean surface distance, and Dice coefficient for the segmentation job to assess the tumor segmentation's accuracy.

Furthermore, a sensitivity analysis was conducted to assess the model's resilience to changes in the hyperparameters and the quantity of modalities utilized. As part of this investigation, the model's performance was tested under several combinations of hyperparameters, including learning rate, batch size, and number of epochs. Additionally, we did performance tests on the model with one to three modalities, varying in number.

4 RESULTS

This section presents the comprehensive findings of our study, evaluating the efficacy of our proposed multi-modal CNN model combined with ChatGPT for automatic brain tumor segmentation and identification. Through rigorous experimentation and analysis, we assess the performance and capabilities of our integrated approach in detail, shedding light on its potential impact on medical imaging and clinical practice.

4.1 Dataset description

In order to promote the creation of cutting-edge techniques for brain tumor segmentation, the BraTS (Brain Tumor Segmentation) dataset was employed in this investigation [12]. The dataset comprises MRI scans from many institutions of individuals with brain tumors, comprising 210 cases of high-grade glioma and 75 cases of low-grade glioma. Four distinct MRI sequences are included in the dataset: fluid-attenuated inversion recovery (FLAIR) images, T1-weighted, T2-weighted, and T1-weighted with gadolinium contrast enhancement. A panel of experts reviewed the ground truth tumor segmentation masks, which several highly skilled radiologists developed. A total of 285 MRI scans with matching ground truth tumor segmentation masks are included in the collection. A training set of 199 MRI scans and a testing set of 86 MRI scans were created from the dataset. Moreover, the dataset comprises patient age, gender, and tumor location information. The dataset has been widely used in the medical image analysis community and is considered a benchmark dataset for brain tumor segmentation tasks.

4.2 Evaluation of model performance

The testing dataset was used to assess the multi-modal CNN model with ChatGPT integration after it had been trained on the training dataset. Numerous metrics, such as the Hausdorff Distance (HD), F1 score, Sensitivity (SEN), Specificity (SPE), and Dice Similarity Coefficient (DSC), were used to assess the model's performance.

We conducted a performance comparison between our suggested method and various other methods in order to assess its efficacy in brain tumor detection and segmentation. We considered several cutting-edge techniques, such as BRATS-2, DeepMedic, and U-Net [13]. U-Net stands out as a popular convolutional neural network architecture tailored for medical image segmentation. Its distinctive design, characterized by skip connections, enables the preservation of spatial information and has proven effective in various segmentation tasks. Similarly, DeepMedic is another notable convolutional neural network architecture specifically crafted for processing medical images. It employs a dual pathway architecture, facilitating the capture of both local and contextual information, thereby enhancing segmentation accuracy. Moreover, BRATS-2, an earlier version of the BraTS dataset, has been pivotal in the development of numerous techniques for brain tumor segmentation.

On the testing dataset, we evaluated the performance of our suggested method with these current approaches using a number of assessment measures, such as DSC, SEN, SPE, HD, and F1 scores. The Table 1 below displays the outcomes:

Table 1. Comparison of brain tumor detection and segmentation performance between proposed method and existing methods

Method	DSC	SEN	SPE	HD	F1 score
Proposed Method	0.89	0.92	0.98	5.48	0.90
U-Net	0.82	0.85	0.96	9.73	0.83
DeepMedic	0.84	0.87	0.97	8.62	0.85
BRATS-2	0.77	0.82	0.92	12.39	0.78

The results unequivocally show that, in addition to obtaining a lower HD, our suggested strategy beats the current DSC, SEN, and SPE methods. 1. The lower HD achieved by our method can be attributed to several factors. Firstly, the incorporation of a multi-modal CNN model allows for the integration of information from multiple imaging modalities, such as T1-weighted, T2-weighted, and FLAIR sequences, which enhances the accuracy of tumor segmentation. Additionally, the utilization of advanced preprocessing techniques, including intensity normalization and skull stripping, ensures that the input data is optimized for accurate segmentation. Furthermore, the integration of the ChatGPT chatbot interface enables clinicians to provide additional insights and refine the model's predictions, leading to improved segmentation accuracy. Furthermore, our suggested approach had an F1 score of 0.90, surpassing that of the other approaches. The employment of a multi-modal CNN architecture, which can efficiently integrate data from several MRI modalities for more precise tumor detection and segmentation, is responsible for the better performance of our suggested strategy. Additionally, the inclusion of the ChatGPT chatbot interface offers clinicians a simple and straightforward interface to engage with the model and get more details about the location and features of the tumor.

4.3 Analysis of model interpretation

The integration of the ChatGPT chatbot interface with our multi-modal CNN model offers a unique opportunity to delve into the intricacies of the model's decision-making process and enhance its interpretability. Through in-depth analysis and interpretation, we gain valuable insights into how the model perceives and interprets complex medical imaging data, empowering clinicians with a deeper understanding of the underlying rationale behind its predictions.

Clinicians leveraging the chatbot interface can effectively navigate through the model's interpretation, gaining clarity on the features and patterns it identifies as indicative of brain tumors. By elucidating the logic behind the model's predictions, the chatbot facilitates more informed decision-making, enabling clinicians to validate the model's findings and identify any potential biases or limitations.

Our analysis of the chatbot's interpretation reveals intriguing patterns in the model's focus areas, with specific brain regions exhibiting heightened significance in tumor detection. These findings align with prior research indicating the propensity of certain brain regions to harbor tumors, underscoring the clinical relevance of our model's insights.

Moreover, the chatbot interface serves as an invaluable tool for clinicians to interrogate the model's decision-making process, fostering trust and confidence in its predictions. By providing an intuitive and user-friendly interface for model interpretation, the chatbot empowers clinicians to engage with the AI system more effectively, facilitating collaborative decision-making and enhancing overall patient care.

In summary, the integration of the ChatGPT chatbot interface enhances the predictability and interpretability of our multi-modal CNN model, offering clinicians a powerful tool for navigating complex medical imaging data. By leveraging the insights provided by the chatbot, clinicians can make more informed decisions, ultimately leading to improved patient outcomes and healthcare delivery.

5 DISCUSSION

The findings reported in the preceding section show how the suggested multi-modal CNN model and ChatGPT chatbot interface can be used to detect and segment brain tumors automatically. The model's high accuracy on the BraTS dataset indicates that it may effectively detect and classify brain cancers using a range of imaging modalities.

These findings have important ramifications for both clinical and research applications. Brain tumor patients can benefit from early diagnosis, treatment planning, and patient monitoring when brain tumors are accurately and efficiently detected and segmented. Furthermore, the suggested model might be modified for medical imaging applications other than identifying brain tumors.

It is important to recognize that the study has certain limitations, even with the encouraging outcomes. First off, the model's applicability to other datasets or clinical contexts may be limited because it was only tested on one dataset. More validation on bigger and more varied datasets is required to determine the model's actual potential. Furthermore, only a limited sample of doctors was employed to evaluate the chatbot interface used for model interpretation; hence, future research should try to evaluate its usability and usefulness on a broader scale.

Regarding potential avenues for future research, there are several that may be investigated. One approach would be to look at using different machine learning algorithms or further improve the model's hyperparameters. An alternative course of action would be to add more clinical information, such as patient demographics or clinical history, to improve the model's accuracy and applicability in clinical settings.

Continued research efforts in these areas not only advance the frontier of medical imaging but also hold the promise of catalyzing paradigm shifts in clinical decision-making and patient care delivery. Our work represents a significant step towards harnessing the synergistic potential of artificial intelligence and natural language processing in transforming healthcare delivery, with far-reaching implications for improving patient outcomes and advancing medical science.

6 CONCLUSION AND FUTURE WORK

This study presents a comprehensive exploration of a novel methodology designed to revolutionize brain tumor detection and segmentation. By seamlessly integrating a multi-modal CNN model with the ChatGPT chatbot interface, we have developed a sophisticated system that offers unprecedented precision and interpretability. This integration allows physicians to delve deeply into the decision-making process of the model, providing them with nuanced insights that can significantly enhance patient care.

Our approach was rigorously evaluated using the BraTS dataset, a widely recognized benchmark in the field of brain tumor segmentation. The results of our evaluation revealed remarkable performance surpassing that of existing techniques. Specifically, our method demonstrated superior accuracy and efficiency, achieving a notable Dice score of 0.89 for tumor segmentation. This outstanding performance underscores the potential of our approach for widespread clinical adoption.

Looking ahead, there are several avenues for future research and development. Firstly, we aim to explore the scalability and generalizability of our methodology by testing it on larger and more diverse datasets. Additionally, further optimization of the multi-modal CNN architecture and integration of advanced natural language processing techniques could enhance the model's performance even further.

Furthermore, we recognize the importance of incorporating feedback from clinicians and experts in the field to refine and tailor our approach to specific clinical needs. This iterative process of refinement and validation will be crucial in ensuring the practical applicability and real-world effectiveness of our methodology.

In summary, while our study represents a significant advancement in the field of brain tumor analysis, there is still much work to be done. By continuing to innovate and refine our methodology, we can further enhance its potential impact on patient care and medical imaging practices.

7 AUTHOR CONTRIBUTIONS

Soha Rawas: Conceptualization, Methodology, Formal Analysis, Writing—original draft, Writing—review and editing. **Agariadne Dwinggo Samala:** Conceptualization, Visualization, Supervision, Writing—review and editing.

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