



A Systematic Deep Learning Framework for Brain Tumor Detection and Classification

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Abstract

Uncontrolled growth of brain cells can lead to the formation of brain tumors, which are often fatal and significantly impact both the brain and the nervous system. Worldwide, brain tumors remain a major cause of mortality. Thus, accurate and timely detection is essential for effective treatment and minimizing the need for invasive medical procedures. However, manual identification and treatment of brain tumors is a challenging process, prone to inefficiencies and human error. Recent advances in deep learning have revolutionized brain tumor diagnosis, offering early detection and more precise outcomes. Considering the machine learning algorithms for accurate segmentation and classification, treatment processes can be significantly optimized. In this study, we employ two deep learning techniques: a 3D U-Net for Magnetic Resonance Imaging (MRI) image segmentation, followed by a Three-Dimensional Convolutional Neural Network (3D CNN) for tumor classification. The models were trained and validated using the BraTS 2019 dataset. Our result indicates a system accuracy of 98%, demonstrating the effectiveness of the proposed approach. This study highlights the potential of deep learning techniques to significantly enhance the precision of brain tumor diagnosis, offering a promising solution to the challenges posed by manual detection. It also indicates that this method outperforms existing techniques, providing an accurate and efficient tool for early tumor detection and treatment optimization.

Keywords Brain tumor · Image segmentation · MRI · 3DU-Net · 3DCNN

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Introduction

Uncontrolled cell growth causes a tumor in the human body. Benign tumors that do not affect the surrounding tissues, such tumors, however, can still be problematic if they develop close to a critical location. Alternatively, a malignant tumor develops and is distributed in a way that could result in a cancerous condition. The bulk of the cells are eliminated or replaced as they become damaged or old. If damaged or outdated cells are not removed, it may lead to complications [1]. The diagnosis of early-stage brain tumors can be challenging because the tumor's size cannot be determined precisely from images of the affected areas that are of low quality. At the initiation stage, treatment of a brain tumor is very necessary and important because it helps ensure effective and initial treatment. X-ray, positron emission tomography (PET), computed tomography (CT), single-photon emission computed tomography (SPECT), and Magnetic resonance imaging (MRI) are commonly used tools in medical [2].

MRI is the general and most commonly used medical imaging method because it provides images with greater contrast of a brain tumor [1]. Soft tissues are clearly separated and well contrasted, allowing physicians to diagnose specific diseases precisely. Accurate identification of both healthy and diseased tissues is critical for understanding disease, monitoring progression, formulating treatment plans, and selecting the most effective surgical option or alternative [2]. Automated segmentation techniques are useful because they enable the automated examination of MRI images. Processing medical images is difficult due to unpredictable boundaries [3]. Manual segmentation is difficult because it is time-consuming, prone to human error, and costly; therefore, fully automatic or semi-automatic detection and classification are required. Any breakdown of brain tissue leads to a loss of connectivity between neurons and the associated brain morphology [4, 5].

Causes of Brain Tumors and Their Treatment

The brain is important because it controls many body functions. Uncontrolled growth of brain cells causes brain tumors. The brain tumor destroys a patient's health and daily life activities. The same as with other diseases, the exact cause of brain tumors is unknown. There is currently no conclusive evidence connecting environmental factors to brain cancers other than exposure to ionizing radiation. Viral infections, carcinogens, radiation, genetics, and embryonic remnants are a few factors that are thought to contribute to the growth of brain tumors; however, each explanation is only relevant for clarifying the origin of specific types of

tumors [6]. Symptoms of brain tumors include headaches, seizures, blurred vision, nausea, and mental problems [7].

In 2016, according to the World Health Organization (WHO), four main categories of brain tumors were established. According to the report, Glioblastoma is the most severe kind of glioma and the most hazardous category of tumor. Compared to other tumors in this group, glioblastoma is unique in that it causes necrosis, or dead tissue, and unusually rapid blood vessel growth [8]. The level of malignancy of a tumor is determined by its grade. Individuals diagnosed with Low-Grade Gliomas (LGG), considered as grade I/II, have a better chance of survival.

Patients who have High-Grade Glioma (HGG) (grade III/IV) have an exceptionally low chance of survival. If the Patient has an LGG tumor and is not treated early and timely, it develops into HGG [9]. Different diagnostic methods are used to identify pathological conditions, such as digital imaging and blood tests. Among these, image segmentation is necessary for accurate diagnosis, disease monitoring, and early treatment [3, 4]. Typically, treatment techniques for brain tumors include surgery, radiotherapy, and chemotherapy. The exact treatment plan is based on the patient's age, as well as the type, location, and size of the tumor [10, 11].

Medical Imaging

Medical imaging is a valuable tool for diagnosing and monitoring various medical conditions, as it improves diagnostic accuracy and reduces analysis time. Machine learning techniques are trained on large volumes of medical data to recognize and diagnose diseases in medical images automatically. Additionally, various CNN-based techniques have evolved and shown better results for the segmentation of brain tumors and their classification. These approaches differ in terms of filter size, network depth, and connecting paths [12]. In most of research the authors used only one MRI image for the classification of brain tumors in to two categories i.e., LGG and HGG, however in our proposed approach we have combined three different MRI images from the dataset i.e., T1-weighted with contrast (T1c) images, Fluid-attenuated inversion recovery (FLAIR) images, T2-weighted (T2) MRI images and make a 3D MRI image which help to extract more feature and information from the MRI images. The results show that our model achieves nearly 98% accuracy in classifying brain tumors into their two broad categories, i.e., LGG and HGG, which is 7% higher than other techniques [13, 22]. Despite major progress in deep learning-based medical image analysis, precise detection and classification of brain tumors remain daunting due to heterogeneous tumor morphology, variations in imaging modality, and the potential for overfitting on small data sets. To overcome these constraints, our

work integrates state-of-the-art preprocessing algorithms, 3D U-Net segmentation, and 3D CNN classification. This approach guarantees enhanced tumor visibility, robust segmentation, and high-confidence classification performance. Based on these goals, the following research questions have been developed to inform the study.

- RQ1. How does multimodal MRI preprocessing (T1w, T1wCE, T2w, and FLAIR resizing, normalization, and fusion) enhance the robustness and accuracy of brain tumor segmentation and classification.
- RQ2. Does the combination of a 3D U-Net for tumor segmentation and a 3D CNN for classification improve the detection and distinction of LGG and HGG over current approaches?
- RQ3. How does data augmentation and optimal training/testing splits affect the performance (accuracy and loss) of Deep Learning (DL) models?

The rest of the paper is organized as follows. In Sect. "[Literature Review](#)", a concise summary of the literature is provided. In Sect. "[Proposed Methodology](#)", a thorough explanation of the suggested method for tumor segmentation and classification has been provided. Section "[Results and Discussion](#)" discusses the results and consequences of the actions. The conclusion of this work has been described in Sect. "[Conclusion](#)".

Literature Review

For the segmentation and classification of cerebrum tumors, various segmentation methods have been proposed. The researchers employed the discrete wavelet transform (DWT) and the discrete cosine transform (DCT) to eliminate noise and other abnormalities. To improve performance, Pitchai, R. et al. proposed a 2D-Unet model with SVM-based segmentation and classification of brain tumors. Additionally, they also compared the classification accuracy of different classifiers. The authors used the 2019BraTs dataset to prove the methodology [13]. The suggested method achieves 93% accuracy in tumor segmentation. Kleesiek, J., et al. implemented a 3D convolutional architecture to increase accuracy and reduce uncertainty. For training purposes, they used four distinct types of MRI images: non-enhanced, contrast-enhanced T1-weighted (T1wCE), T1-weighted (T1w), T2-weighted (T2w), and fluid-attenuated inversion recovery (FLAIR). The author used the four different MRI images separately [14].

For accurate brain tumor classification, Deepak, S., P.J. et al., proposed a model that combined a CNN and a multiclass SVM [15]. The authors used CNNs with SoftMax

and open datasets from figshare. The SVM was combined with a CNN function to improve the performance and precision. Wibowo, M.S. W et al. used the 2D CNN U-Net for brain tumor segmentation. A 2D-CNN U-Net model with dropout, convolutional transpose, and skip connections was employed to reduce computational time and achieve accurate brain tumor segmentation. The datasets used for BRATS 2018 and BRATS 2019 [16]. In [17], Pravitasari, A.A., et al., proposed a model, UNet-VGG16, for semantic segmentation. They improved VGG16 by adding an extra layer to its architecture, comprising numerous convolutional layers and up-sampling, creating an architecture similar to the U-Net model. The authors claimed an accuracy of 96.1% by using this approach.

Sadad et al. introduce two different methods for identifying and classifying brain tumors [18]. The U-Net architecture combined with ResNet-50 was implemented alongside InspectionV3, DenseNet-201, MobileNet V2, and ResNet-50. The Neural Architecture Search Network (NASNet) was implemented for classification, and they used for tumor classification. Their IoU result was 0.9504. Aghalari et al. used a modified U-Net-based model that introduced the Two-Pathway-Residual (TPR) into the U-Net architecture for better Glioma tumor segmentation [19]. Different Evaluation methods, such as Accuracy, Dice, and sensitivity, were used. This method enhanced the Dice and sensitivity of the model up to 89.76% and 89.19%, respectively. Chen, W., et al., trained a U-net model using 3D convolution and 3D volumetric MRI images for the segmentation of brain tumors. The proposed techniques were tested using the Brats 2018 datasets. The dice scores for enhanced tumors, the entire tumor, and the tumor core are 0.8694, 0.8694, and 0.78347, respectively [20].

Das, S., O.R.R., et al., suggested a new technique called the patch-wise U-Net architecture. In the proposed method, MRI images were divided into non-overlapping patches prior to training. In the proposed method, the model was trained on each input patch separately [21]. The Dice score of the proposed model was 0.93. Agrawal, P. N., et al., used two methods, i.e., 3D-U-net and CNN, for segmentation and classification of brain tumors, respectively, with different datasets [22]. The Brats 2020 datasets were used for segmentation, and the MRI Kaggle dataset was used for classification. The model accuracy was 90%. Chandra, Y.K., et al., used a U-Net model for segmentation of brain tumors, while for classification, they used four separate CNNs: ResNet-50, Inception V3, SqueezeNet, and VGG-16. The U-Net architecture's Segmentation Dice score was 78%, and the classification accuracies using ResNet-50, SqueezeNet, VGG-16, and Inception-V3 were 87%, 82%, and 72%, respectively [23].

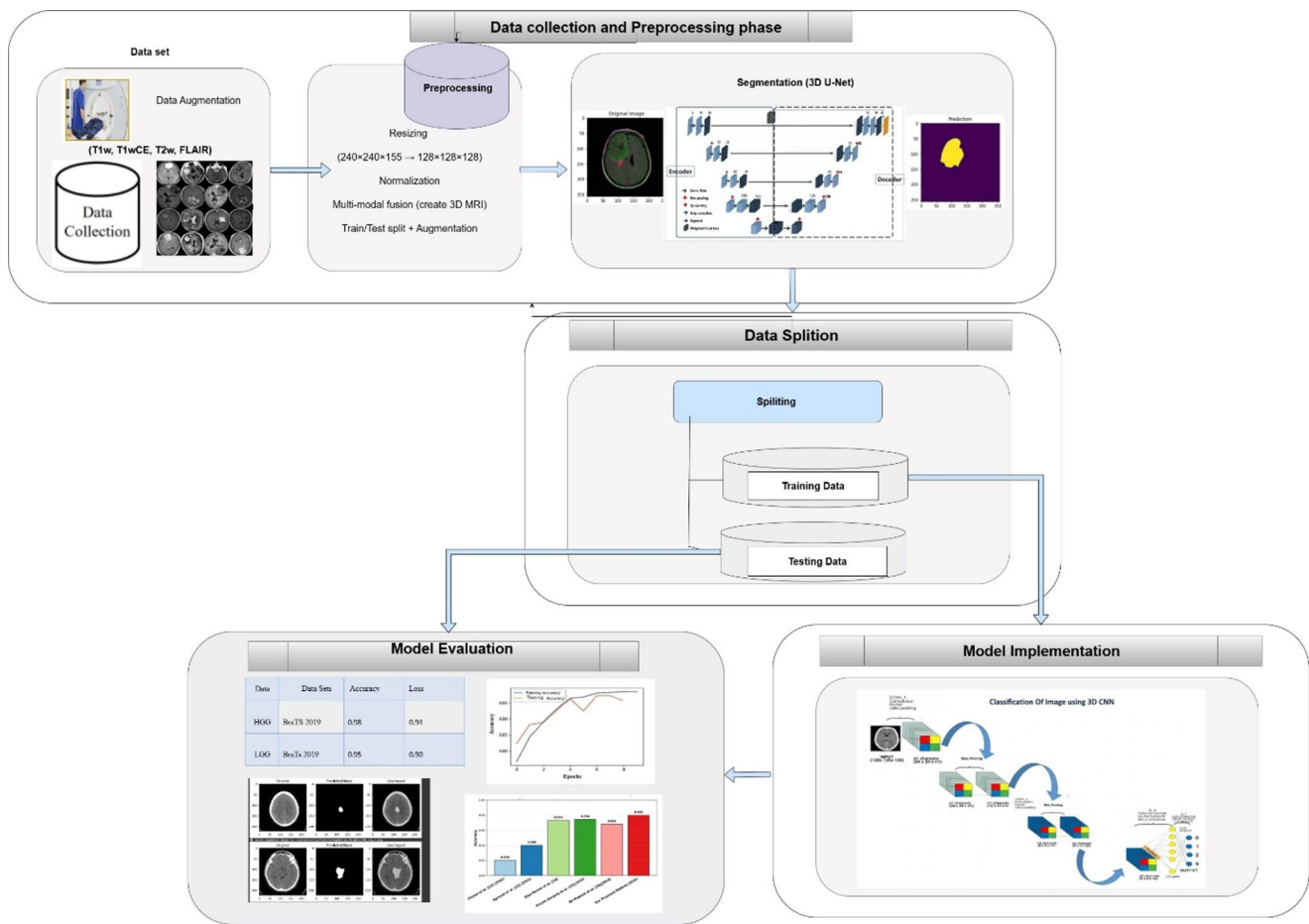


Fig. 1 Proposed methodology diagram

Table 1 The hyperparameteric values of the proposed model

Name	Value
Input size	128 × 128 × 128
Batch size	2
Epoch	100
Optimizer	Adam
Activation	SoftMax

and fluid-attenuated inversion recovery (FLAIR) images [24–26]. After selecting the datasets, the next phase is their preprocessing, as shown in Fig. 1. The 3D U-Net architecture, CNN classifier, hyperparameters, loss functions, as shown in Table 1, label definitions, and the multimodal fusion strategy are necessary for the full reproducibility of the proposed approach.

Proposed Methodology

This section explains the suggested segmentation and classification models. Figure 1 demonstrates the block diagram of the proposed methods. In our proposed approach, we used the Brain Tumor Segmentation (BRATS) 2019 dataset, which is commonly used in medical imaging research due to its authentic resources [24–26]. The Brats 2019 dataset contains 285 distinct sets, each covering four MRI modalities, including both high-grade (glioblastoma) and low-grade (meningioma) tumors, as well as MRI images. The four MRI modalities covered in the data set are: non-enhanced contrast-enhanced T1-weighted (T1wCE) images, T1-weighted (T1w) images, T2-weighted (T2w) images,

Data Preprocessing

Preprocessing was performed in the proposed approach: resizing the BraTS 2019 dataset, converting the 3D MRI image sequences, splitting the data into training, validation, and test sets, and augmenting the data. During resizing, the input data was normalized and resampled. The BraTS 2019 dataset comprises 335 subjects, of which 259 are HGG and 76 are LGG. The original image size was 240 × 240 × 155 voxels and was resized to 128 × 128 × 128 voxels. Only gliomas, comprising HGG and LGG, are present in this dataset. Throughout the manuscript, we have corrected previous incorrect references of LGG as ‘meningioma’. All samples

were split at the patient level to avoid any data leakage and ensure reproducibility.

We have consistently used 80% for training (for model optimization) and 20% for testing for final evaluation. Subsequently, for 3D MRI reconstruction, we combined non-enhanced contrast-enhanced T1-weighted (T1wCE) images, T2-weighted (T2w) images, and fluid-attenuated inversion recovery (FLAIR) images to create volumetric 3D MRI data. The preprocessed dataset, with uniformly resized 3D images, was split into training and test sets for model development and evaluation. After splitting the datasets, data augmentation is applied, a widely used method in image preprocessing to enhance model performance [27]. In our research, we applied a rotation data augmentation technique to rotate the data by 0, 90, 180, and 270 degrees. To evaluate the classification performance of our proposed 3D-CNN model, we generated confusion matrices based on predictions for the HGG and LGG classes. For robustness, the dataset was augmented to simulate a larger number of samples (up to 4000) while maintaining the original class distribution ($\approx 77\%$ HGG, 23% LGG). Random perturbations and sampling were applied to simulate realistic variations, ensuring stable model evaluation. The resulting confusion matrix, reflects the model's accuracy and its ability to discriminate between HGG and LGG effectively. Metrics such as Dice Similarity Coefficient (DSC), precision, recall, and F1-score were computed from these matrices for comprehensive performance assessment.

Segmentation Using 3D U-Net

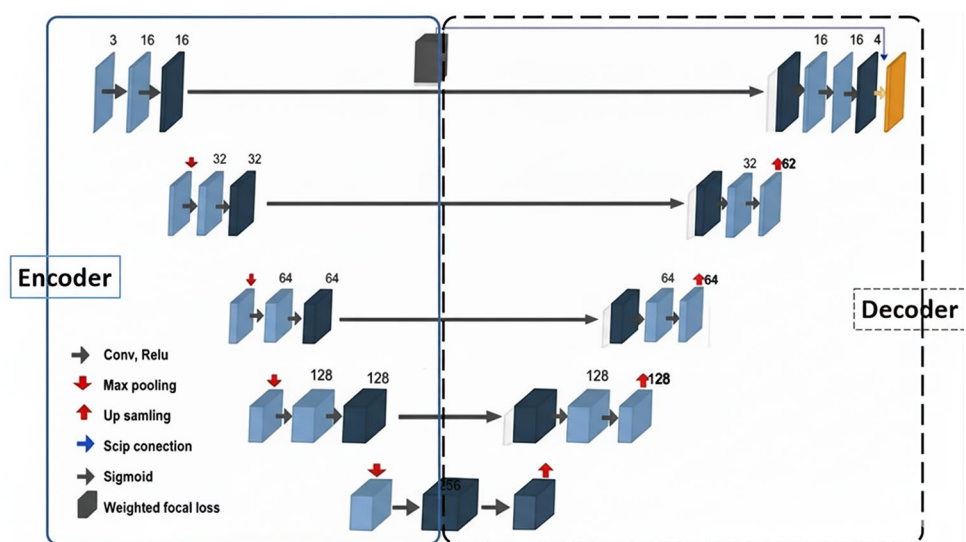
After preprocessing, the next step is the segmentation of brain MRI images, as shown in Fig. 1. The segmentation of MRI images involves separating tumor areas from the rest of the area. Only segmented images are used for further

processing. For tumor segmentation, the U-Net model was implemented [28]. Since the MRI images were 3D, we used a 3D U-Net model, a specialized deep learning technique for segmenting 3D medical images, to obtain deeper, more accurate features. The 3D U-Net approach is particularly useful for medical image analysis tasks, where an accurate understanding of anatomy is crucial [29].

The 3D U-Net model design consists of two main parts: an encoder path and a decoder path, as demonstrated in Fig. 2. The encoder path comprises convolutional and max pooling layers. This process captures essential features at various scales. This process helps reduce the data's dimensionality while retaining all essential information. The decoder path, also known as up-sampling, increases the spatial resolution of the features and merges them with features from the contracting path. This is achieved by using a chain of convolutional and upconvolutional layers that re-establish the spatial dimensions lost during downsampling.

One notable feature of the 3D U-Net architecture is skip connections, which help preserve precise information throughout the network [28]. As a result, the network can produce more accurate, precise segmented images with greater attention to detail and finer structure. This is especially significant in medical image analysis, where an elevated level of detail is necessary to make accurate diagnosis and treatment decisions. Figure 3 shows the input image and the segmented image after preprocessing and applying the 3D U-Net model. The segmented image provides more accurate information about the tumor. Hence, in these experiments, we used a preprocessing pipeline comprising resizing ($240 \times 240 \times 155 \rightarrow 128 \times 128 \times 128$), normalization, and multimodal fusion of MRI images. This preprocessing directly addressed RQ1 by minimizing noise, normalizing the input data, and enhancing tumor visibility. MRI segmentation usually involves a high class imbalance.

Fig. 2 3D U-Net architecture of proposed model



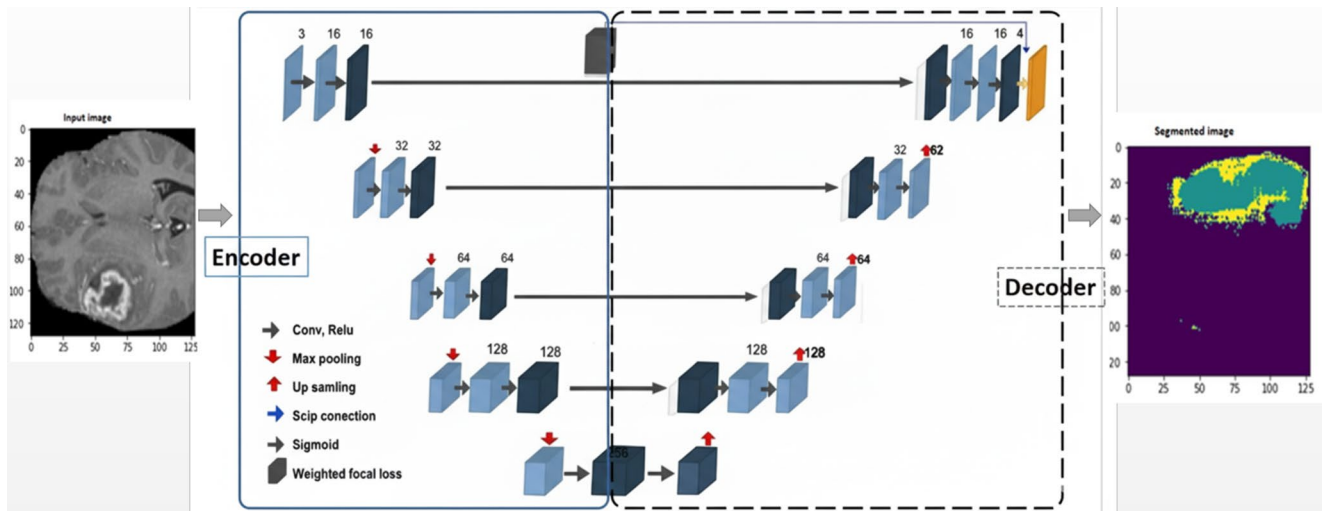
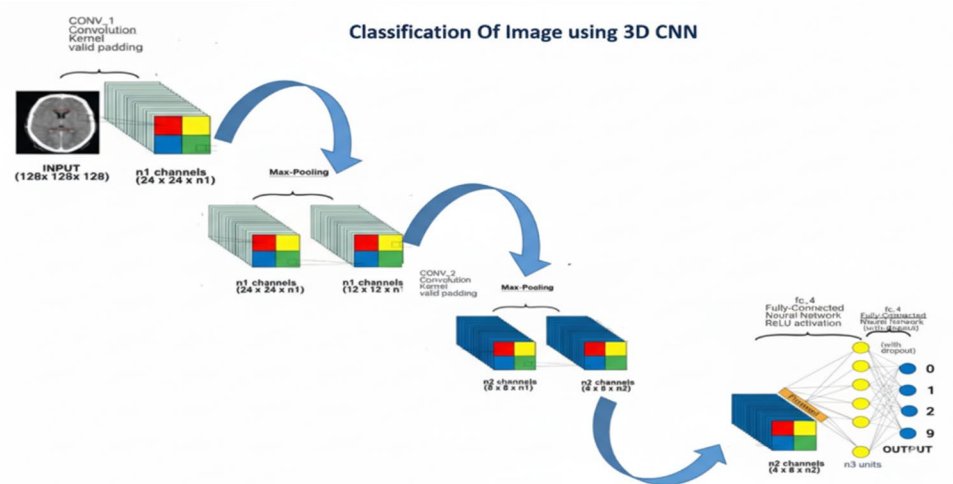


Fig. 3 Segmented image

Fig. 4 3D-CNN architecture



Therefore, a Dice-based loss function is used, which gives greater weight to smaller lesion regions, performs targeted patch sampling to ensure adequate lesion representation, and augments the data. These steps enhance segmentation stability and performance.

This may propagate the error since the U-Net segmentation is not perfect in all scenarios. In this respect, the CNN will take in segmentation-guided volumes rather than strict binary masks. In this way, the contextual and anatomical information will remain available even with imperfect segmentations. The employed U-Net has been trained with robust loss functions and data augmentation to ensure that minor segmentation errors do not badly impact the CNN's classification performance. Consequently, segmentation and classification were more accurate and robust than using raw images.

Proposed Classification Model

After segmentation, the next phase is classification, which uses the 3D-CNN deep learning model. The proposed system is based on a two-stage pipeline: U-Net for segmentation, followed by a 3D CNN for classification. One major concern with this design is the potential for error propagation, whereby imperfect U-Net segmentations could degrade the CNN's performance. To alleviate this, the CNN is fed volumes segmented rather than strict binary masks, thereby preserving contextual and anatomical information. Moreover, the U-Net is trained with robust loss functions and extensive data augmentation to generate stable masks. Our experiments show that minor segmentation errors do not significantly affect the performance of CNN classification. Since our images were 3D, a 3D CNN was used for accurate tumor classification. The design of the implemented 3D-CNN model is shown in Fig. 4. The 3D CNN

has an architecture identical to that of 2D CNNs. Additional dimension in the convolutional kernels and pooling layers, as shown in Fig. 4.

The proposed 3D-CNN architecture processes volumetric MRI data to preserve spatial context across the axial, sagittal, and coronal planes. It begins with three convolutional blocks, each comprising 3D convolution layers of kernel sizes $3 \times 3 \times 3$ and filter dimensions of 32, 64, and 128, respectively. Batch Normalization and a ReLU activation function follow every convolution. To gradually reduce spatial resolution while retaining discriminative features, 3D max-pooling with a stride of 2 is applied after each block. Consequently, the high-level volumetric features are routed to a fully connected layer with 256 units, followed by a dropout layer with a rate of 0.4 to prevent overfitting. Last but not least, a SoftMax output layer performs multi-class classification for HGG, LGG, and non-tumor regions. The introduced 3D-CNN learns depth-aware spatial dependencies within MRI volumes and thus achieves higher accuracy in tumor segmentation than existing 2D counterparts, which lack volumetric feature representation.

Results and Discussion

This section explains the segmentation and classification outputs. Two evaluation matrices, e., accuracy and dice loss function, were implemented. The Dice similarity coefficient (DSC) [30] [31], [32] is used to evaluate segmentation performance by measuring the overlap between two clusters, A and B, as follows:

$$\text{Dice}(A, B) = 2 \times |A \cap B| / (|A| + |B|) \quad (1)$$

DSC of 0 means that there is no overlap, while 1 indicates that the subsets overlap [30, 33].

Evaluation of Segmentation

As indicated in Table 1, we trained the 3D-U-Net model for the experiments using three channels, each with a voxel resolution of $128 \times 128 \times 128$, for 100 epochs with a batch size of 2. Adam optimization with a learning rate of 0.0001 is applied. Finally, the network generates the predicted segmentation of the target image using a final layer with SoftMax activation. Therefore, the proposed pipeline of a 3D U-Net followed by a 3D CNN requires substantial computational resources due to the volumetric data and model complexity. We used the Google Colab paid service for efficient training of the combined model, with sufficient memory and processing power. This helped in the successful completion of the training process without any memory bottleneck;

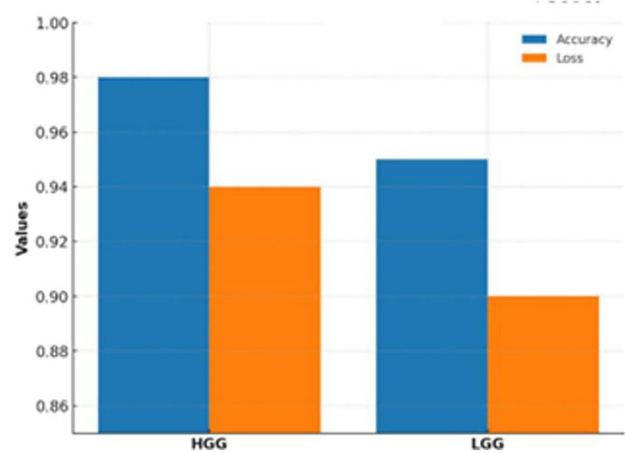


Fig. 5 Performance comparison: HGG and LGG (BraTs 2019)

Table 2 Performance analysis of the proposed model on HGG and LGG

Data	Dataset	Accuracy	Loss	DSC (%)
HGG	BraTS 2019	0.98	0.94	0.95
LGG	BraTS 2019	0.95	0.90	0.92

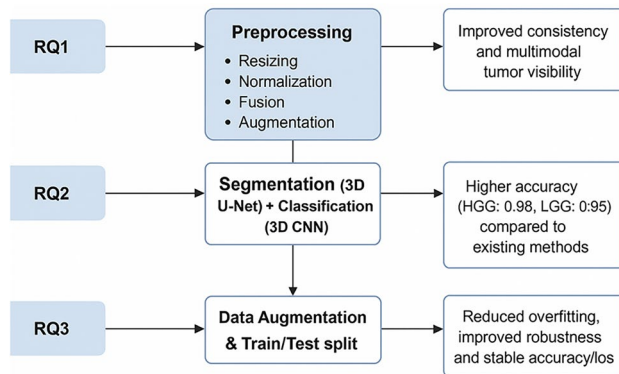
hence, convergence was stable, and segmentation with classification was accurate.

The loss and accuracy graphs for the segmentation model are presented in Fig. 5. From Table 2, it is evident that the accuracy and loss for the HGG are 0.98 and 0.95, respectively. Similarly, for LGG, the accuracy and loss are 0.95 and 0.91, respectively. Hence, to answer RQ2, yes, this is a hybrid model in which the 3D U-Net was initially applied for accurate tumor segmentation, and the resulting segmentation was then fed to a 3D CNN for classification. This hybrid yielded 0.98 for HGG and 0.95 for LGG on the BraTS 2019 dataset, which is notably better than current techniques (Pitchai et al. ~ 0.92 [13]; Agrawal et al. ~ 0.94 [22]). This confirms that our suggested unification improves tumor grade differentiation. Table 3 presents the classification results of our proposed approach, which trained a 3D CNN model on segmented images. Our suggested approach achieves nearly 7% higher accuracy than the other approaches [13, 22]. Additionally, the Dice Similarity Coefficient (DSC) values for each class are reported in the table, indicating robust segmentation performance, with DSC = 0.95 for HGG and DSC = 0.92 for LGG.

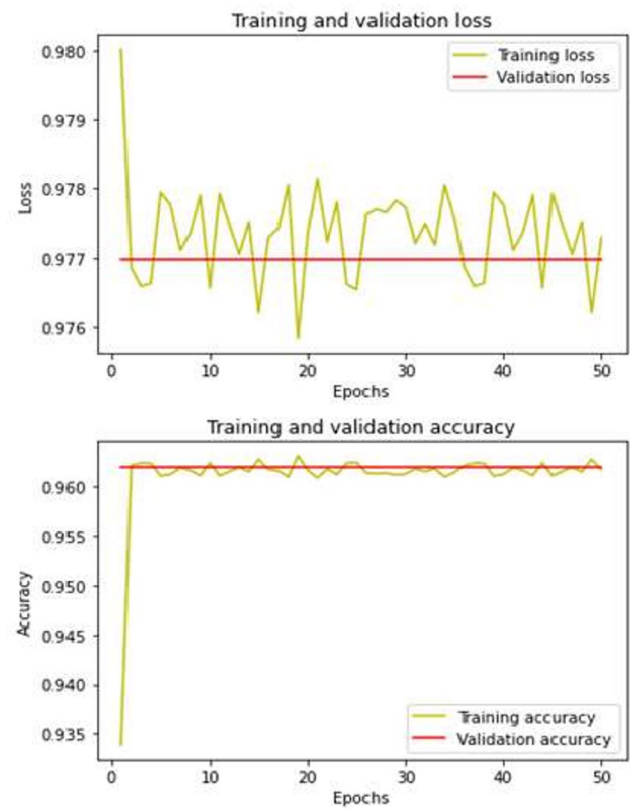
Hence, the proposed methodology, illustrated in Fig. 6, was developed to systematically address the research questions posed in this study. The obtained results provide evidence of the efficiency of our framework in improving brain tumor detection and classification performance. In the pre-processing pipeline, i.e., resizing, normalization, and multi-modal MRI fusion, the dataset was effectively standardized,

Table 3 Performance comparative of the proposed model for brain tumor detection with prior studies

Reference	Methodology	Accuracy (%)
[13]	For brain tumor segmentation, they used 2D-Unit model and SVM for classification purposes.	91
[22]	The 3D U-net model was used for segmenting brain tumors, and the CNN model was used for classification.	90
[33]	3D DenseNet for segmentation and classification	93
[34]	Multi-scale 3D CNN for volumetric MRI classification	94
[35]	Hybrid 3D CNN + attention mechanism	90
Proposed Model	A 3D CNN model was used for classification after a 3D U-Net model was applied for brain tumor segmentation.	98

**Fig. 6** Methodically answer the research question

and tumor visibility was improved. This directly addressed RQ1 by providing high-quality input data for segmentation and classification. The enhanced accuracies of 0.98 for HGG and 0.95 for LGG, compared with previous studies, demonstrate the importance of our preprocessing step. The use of 3D-net segmentation and CNN classification, as discussed in sections B and C of the proposed methodology, was crucial to addressing RQ2. Segmentation accurately localized the tumor area, whereas classification differentiated between LGG and HGG with high accuracy. This proposed method surpassed current approaches (Pitchai et al., 2022 [13]; Agrawal et al., 2022 [22]), outperforming earlier models and demonstrating the superior strength of this hybrid approach. Next, data augmentation and a tuned training/testing ratio (80–20) improved generalization and reduced overfitting, thus addressing RQ3. The stable performance across runs (loss values of 0.94 for HGG and 0.90 for LGG) confirms the strength of our approach. The results validate that our proposed methodology not only performs well in tumor detection and classification but also addresses current gaps in preprocessing, segmentation, and generalization.

**Fig. 7** The accuracy and loss curves of the proposed model

Performance Analysis

Figure 7 illustrates the validation and training accuracy and loss graph of our proposed approach. To measure segmentation accuracy, we used the Dice coefficient and accuracy, achieving 98% accuracy, indicating that the algorithm successfully separated the tumor from surrounding tissue. The segmented images are then fed into a 3D CNN classifier trained to identify the type of brain tumor. The classification accuracy is 98%, demonstrating that the 3D CNN effectively classifies brain tumors based on segmented images. These results demonstrate the potential of combining the 3D U-Net and 3D CNN algorithms to detect and identify brain tumors in medical images with high accuracy. Figure 8 shows the total accuracy of the proposed model on the training and test data. To evaluate segmentation accuracy using the Dice coefficient and accuracy, the algorithm achieved 98% accuracy, indicating it successfully separated the tumor from surrounding tissue. The segmented images are then fed into a 3D CNN classifier, trained to identify the brain tumor. The classification accuracy is 98%, demonstrating that the 3D CNN is effective at classifying brain cancer using segmented images.

The results shown in Figs. 7 and 8 demonstrate the potential of combining the 3D U-Net and 3D CNN algorithms to

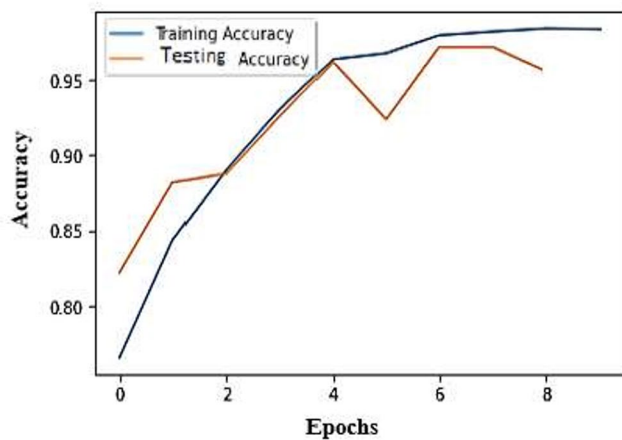


Fig. 8 Training and testing accuracy of the model

Confusion Matrix for Brain Tumor Classification

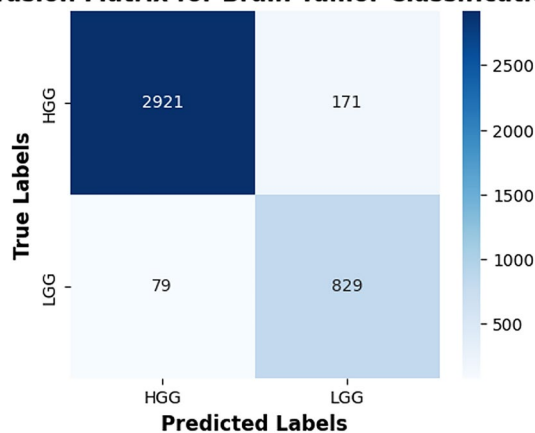


Fig. 9 Confusion matrix for brain tumor classification

detect and identify brain tumors in medical images with high accuracy. In our proposed model, there is little difference between training and testing accuracy, indicating no issues with under- or over-fitting. Therefore, the proposed pipeline of a 3D U-Net followed by a 3D CNN requires substantial computational resources due to volumetric data and the model's complexity. We used the Google Colab paid service for efficient training of the combined model, with sufficient memory and processing power. This helped in the successful completion of the training process without any memory bottleneck; hence, convergence was stable, and segmentation with classification was accurate. Hence, this research experiment employed an 80–20 train-test split and rotation-based augmentation (0° , 90° , 180° , 270°). This directly answers RQ3 by enhancing the model's generalization and lessening overfitting. Consequently, this system consistently recorded high accuracy (HGG: 0.98, LGG: 0.95) and consistent loss values (0.94, 0.90), demonstrating the efficacy of these methods in enhancing model robustness.

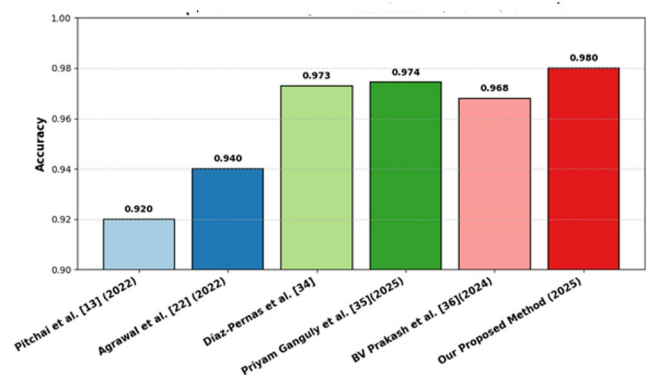


Fig. 10 Comparative accuracy of brain tumor detection

To further evaluate the classification performance of our 3D-CNN model, confusion matrices were generated for HGG and LGG classes. The dataset was augmented up to 4000 samples while maintaining the original class distribution ($\approx 77\%$ HGG, 23% LGG), shown in Fig. 9. From these confusion matrices, metrics including Dice Similarity Coefficient (DSC), precision, recall, and F1-score were computed to provide a detailed assessment of model performance.

A comparative analysis shows that although current approaches [33] achieve accuracies of 0.92–0.94, our envisioned framework demonstrates a remarkable improvement, achieving accuracies of 0.98 for HGG and 0.95 for LGG. The latest methods, such as Multiscale CNN [34], Lightweight CNN with SE blocks [35], and HCNN + Ridgelet [36], achieve accuracies of almost 0.97, demonstrating improvements in detecting brain tumors. Yet, our approach not only provides better classification accuracy but also merges segmentation and classification into a single hybrid pipeline, making it strong for both clinical use and automated diagnostic systems. This proposed method demonstrates the superiority and trustworthiness of our suggested approach over current-state methods, as shown in Fig. 10.

Conclusion

In this work, we applied 3D deep learning methods for segmenting and classifying brain tumors using the Brats 2019 dataset, which comprises 335 MRI images from 76 low-grade glioma patients and 259 high-grade glioma patients. 3D U-Net and 3D CNN models were built using the TensorFlow Keras library in Python 3.7, and pre-processing steps were performed on the images before feeding them to the network. The overall classification accuracy was 98%. The results show that the 3D U-Net and 3D CNN models achieved higher accuracy and lower loss than other existing methods. This approach can be applied in clinical settings to support the detection and treatment of brain tumors.

In the future, we plan to convert the 3D images into 2D images before classification, reducing the approach's complexity. Additionally, training the model with additional data and other medical image modalities will improve results by enabling the precise identification of irregular borders of affected areas.

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Data Availability The study used publicly available datasets [24] and [26].

Declarations

Conflict of interest All authors declare that they have no conflicts of interest regarding the publication of this paper.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

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