



Automated evaluation and parameter estimation of brain tumor using deep learning techniques

B. Vijayakumari¹ · N. Kiruthiga¹ · C. P. Bushkala¹

Received: 19 April 2023 / Accepted: 12 July 2024 / Published online: 16 August 2024
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2024

Abstract

The identification and region extraction of brain tumors is an essential aspect of clinical image analysis and the diagnosis of brain-related illnesses. The precise and accurate identification of tumors from MRI images is particularly significant in the effective formulating of treatments such as surgery, radiation therapy, and drug therapy. The challenge of segmentation stems from the variability in the size, location, and appearance of tumors, making it a complex task. Various segmentation and classification techniques have been created and designed for brain tumor diagnosis; however, these traditional techniques are time-consuming and subjective and require expertise in image processing. In recent times, deep learning-based approaches have shown promising results in brain tumor segmentation. This research aims to develop a brain tumor segmentation and classification model that enables medical professionals to locate and measure tumors accurately and develop effective treatment and rehabilitation strategies. The process involves segmenting the tumor and further classifying it into its two major types. The parameter estimation from the segmented output provides an insight that is pivotal in the evaluation of MRI brain tumors. With further research and development, deep learning-based segmentation and classification could become an important tool for accurate detection and evaluation of brain tumors. The development of deep learning-based segmentation and classification methods can greatly benefit the medical community, and according to the finding from the experiment, it is shown that the proposed framework excels in brain tumor segmentation and classification with an accuracy of 99.3%.

Keywords Brain tumors · Deep learning · Segmentation · Classification · MRI · Medical image analysis

1 Introduction

Brain tumors are unusual development of cells in the brain that can be categorized into two major types: primary and secondary. Primary brain tumors arise from the brain tissue itself and can be either benign or malignant. Malignant primary brain tumors are further categorized as high grade or low grade, based on the tumor's appearance under a microscope and its level of aggressiveness. Secondary

brain tumors, which are commonly referred to as metastatic tumors, arise from other areas of the body and spread to the brain through the bloodstream or lymphatic system.

Meningiomas and gliomas are two types of brain tumors that are often encountered in clinical practice. Meningiomas account for approximately one-third of all primary brain tumors and are usually benign, slow-growing tumors that arise from the meninges. They can occur in any part of the brain, but are most commonly found in the convexity of the brain or near the skull base. Gliomas are tumors that arise from the glial cells that upholds the neurons in the brain. They can be further classified into various groups according to their cellular characteristics, location, and level of aggressiveness. Magnetic resonance imaging (MRI) is commonly utilized for the purpose of analyzing and monitoring of brain tumors. However, the interpretation of MRI images can be challenging, as brain tumors can

✉ B. Vijayakumari
vijayakumari@mepcoeng.ac.in

N. Kiruthiga
viswaiknagajothi_ec@mepcoeng.ac.in

C. P. Bushkala
bushkalacp08_ec@mepcoeng.ac.in

¹ Department of ECE, Mepco Schlenk Engineering College,
Sivakasi, Tamil Nadu, India

vary in size, shape, and location, and can have similar appearances to normal brain tissue.

Lately, deep learning techniques have come to light as a promising approach for the segmentation and classification of MRI images of brain tumors [1]. Deep learning algorithms can be trained on large datasets of MRI images to accurately identify brain tumors and classify them into different types based on their characteristics. Accurate segmentation allows for the precise localization and quantification of tumor volume, which is important for treatment planning and monitoring. Classification of brain tumors based on their cellular characteristics is another important task in the detection and diagnosis of brain tumors. Hence algorithms like deep learning-based approach find its significance in diagnosis in the recent days. Deep learning is a subset of artificial intelligence, which will learn the information given deeply, without explicit programming. While traditional methods cost a lot of manual work, deep learning-based methods can automate the process, reducing the time and effort required for image analysis and improving the consistency and accuracy of the results. Deep learning has proven to be highly significant in the field of brain tumor detection. The convolutional neural network algorithms can learn intricate patterns and features in images that may not be easily discernible by human experts, resulting in more precise and reliable tumor detection. Early detection of tumors, which may not be easily observable by traditional methods, can be handled by deep learning algorithms. It automates the tumor detection process, reducing the burden on radiologists and healthcare professionals. By quickly analyzing large volumes of medical images, these algorithms can expedite diagnosis, saving time and improving overall efficiency in health care.

2 Related works

Several studies have been conducted on the use of deep learning techniques for brain tumor segmentation and classification using MRI images. These studies have explored various deep learning architectures and methodologies and have demonstrated results in improving the precision and efficiency of brain tumor detection and treatment. Most of the articles available are separately discussing about either segmentation or classification. Only a few are discussing detection and classification. These works focus on the application of deep learning and machine learning techniques to detect and extract brain tumor using MRI images. They employ various approaches such as CNN's, random forests, and conditional random fields. Ali et al. proposed a deep network for brain tumor image segmentation [2]. They used a fully connected

neural network (FCN) to segment brain tumors in MRI images. Li et al. [3] also proposed a multimodal fusion-based approach that combined various MRI modalities for brain tumor detection using a convolutional neural network. Pereira et al. proposed a CNN-based approach for brain tumor segmentation in MRI images [4], which utilized both 2D and 3D patches for training. This approach achieved promising results and outperformed other state-of-the-art methods. Shah et al., [5] put forward a robust approach for brain tumor detection using a fine-tuned EfficientNet. Their approach achieved high accuracy in detecting brain tumors in MRI images. Pitchai et al. [6] introduced a method for brain tumor segmentation using deep learning and fuzzy k-means clustering. This method utilized U-Net architecture with the fuzzy k-means clustering algorithm to segment brain tumors in MRI images, and Wang et al. proposed an automatic tumor segmentation method with deep convolutional neural networks [7] for radiotherapy applications. Their approach achieved high segmentation accuracy and potentially assisted medical professionals in treatment planning. H. H. Sultan et al. developed a deep neural network for multi-classification of brain tumor images [8], achieving high accuracy. Another study by W. Wang et al. presented a novel image classification approach [9] using dense-mobilenet models. A machine learning-assisted technique for multiclass classification of malignant brain tumors was proposed by A. Vidyarthi et al. [10], while A. Gumaei et al. introduced a hybrid feature extraction method [11] with regularized extreme learning machine. A deep CNN for brain tumor classification proposed by W. Ayadi et al. [12] achieved high accuracy on a benchmark dataset. Recently, Ramin Ranjbarzadeh et al. presented a segmentation model [13] using deep learning with attention mechanism, which claims for its dice score of 0.9203 within 84 s. A survey paper on deep learning-based brain tumor segmentation analyzed by Zhihua Liu et al. [14] explains the efficacy of it using 150 scientific papers. They have widely investigated the brain tumor task and highlighted the pros and cons of it. The application of federated learning methodologies to enhance global segmentation performance was analyzed in detail by Md Faysal Ahamed et al. [15], and client-based federated model training strategy was also discussed to aid future researchers. In a different dimension, Haq and A.u et al. [16] presented an approach for brain tumor classification alone by improved CNN with transfer learning obtained high accuracy and suits for IoT environment. A survey on brain tumor classification and segmentation with CNN was performed [17] by Díaz-Pernas FJ et al., during the year 2021. They have achieved a tumor classification accuracy of 0.973, higher than the other approaches. In the same year, another review [18] by Biratu ES et al. was done for comparing region growing,

machine learning and deep learning methods to analyze segmentation and classification. An early detection and segmentation was performed by Aggarwal and M et al. [19], (2023). For the BRATS 2020 MRI sample data, they could obtain a 10% accuracy improvement with Resnet.

Overall, these studies demonstrated the potential of deep learning techniques for brain tumor segmentation and classification using MRI images. While the field is still evolving, these studies provide a strong foundation for the development of automated, noninvasive methods for brain tumor diagnosis and treatment. In this research work, a complete and extensive review of the current state-of-the-art deep learning techniques for brain tumor segmentation and classification using MRI images is presented. The different types of deep learning architectures that can be used which will enhance the accuracy and efficiency of these tasks are discussed and the datasets that have been used for training and validation of these models, and the performance metrics used for evaluating the segmentation and classification results are presented. The research work outlined in this paper is emphasized through the following novel contributions. The various deep neural network algorithms were compared and analyzed for brain tumor detection. From the analysis, a novel end-to-end brain tumor segmentation and classification system was devised, which determines the location, identifies and segments the tumor precisely in a short time. Since classification is performed after segmentation, it always produces reliable results. As in the existing systems, though the tumor is identified, it is too hard for the medical practitioners to evaluate and describe the growth of it. By considering this in mind, here a novel evaluation and parameter estimation algorithm has also been proposed, which provides an insight that is crucial in clinical image analysis which were not experimented and explained in the existing literature. As the proposed approach provides improved accuracy, it proves its efficacy.

3 Proposed framework

In this research work, a novel automatic brain tumor evaluation method is proposed using deep learning techniques. The first step in our segmentation and classification system involves preprocessing, for which we have collected and utilized a total of 3929 images. During preprocessing, the images are augmented and resized based on the selected models. The resized MRI images are subsequently fed into the segmentation model, which detects the precise location of the tumor and outputs a tumor mask. This information is then utilized to measure the tumor mass. The system diagram for the proposed automated brain tumor evaluation is portrayed in Fig. 1. For classification, the

images are given as input to the classification model which uses and trains on the data. The segmented output is used for testing the model.

When an input image is given by the user, the classified output displays the type of tumor class that it belongs to among the most popular meningioma and gliomas if a tumor is present else it classifies into no tumor in case of absent tumor mass.

3.1 Preprocessing

Preprocessing MRI brain tumor images is a vital step in clinical image analysis. For this system, two common techniques were used: One of the techniques used is rescaling the images, which involves adjusting the size of the images to enhance fit for it in the used deep learning model. This helps in segmenting the tumor regions accurately. Another important technique is augmentation, which involves generating new training images from the existing ones. Transformations like rotating, flipping, and zooming can be utilized to manipulate images.

3.2 Segmentation

The segmentation of brain tumors from MRI images is a critical first step in the identification and evaluation of brain tumors. The precise identification of the tumor from the brain and segmenting it separately is one of the most essential steps for developing personalized treatment plans. Deep learning segmentation models can learn and identify patterns in large datasets of MRI images, allowing for the automated segmentation of tumors. These methods reduce the time and effort required for image analysis, enhance the consistency and accuracy of results, and decrease the need for invasive procedures. As the field of deep learning continues to evolve, it is likely that these approaches will become increasingly integrated into clinical practice, ultimately leading to better outcomes for patients with brain tumors. The effective segmentation of a model can be evaluated by metrics like IoU (intersection over union), Jaccard coefficient and Dice coefficient which can be calculated using Eq. (1–3)

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

$$\text{Jaccard} = \text{IoU} / (2 - \text{IoU}) \quad (2)$$

$$\text{Dice coefficient} = \frac{2 * |A \cap B|}{(|A| + |B|)} \quad (3)$$

Here A is the ground truth image and B is the predicted image.

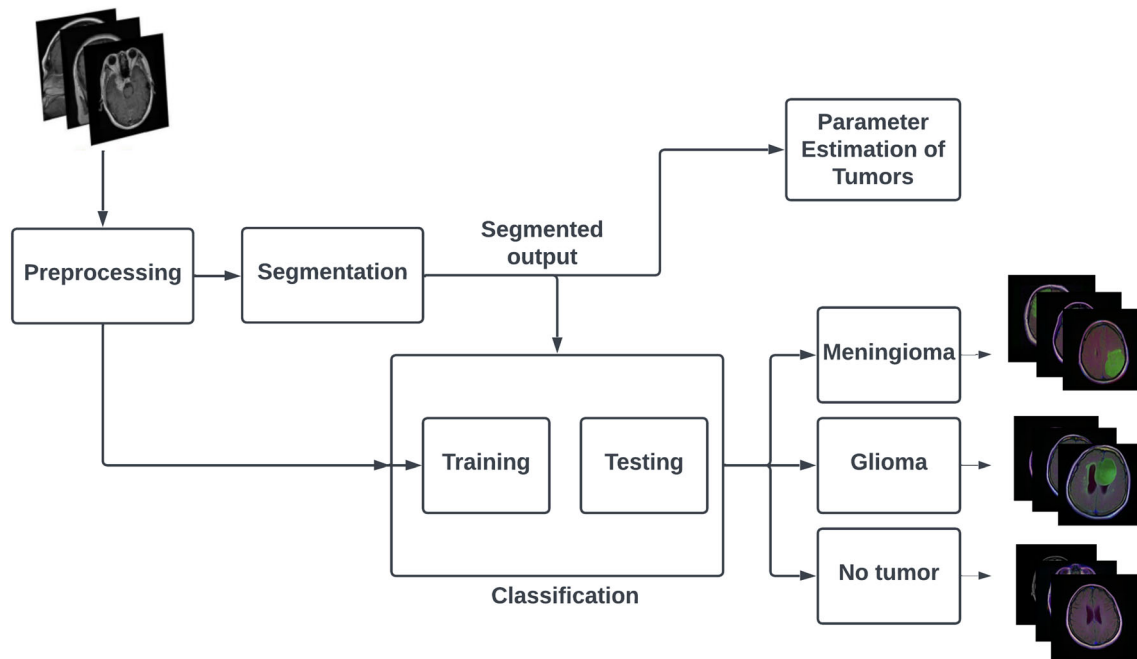


Fig. 1 Schematic diagram of the proposed brain tumor evaluation system

3.3 Classification

Classification of brain tumors based on their cellular characteristics is another important task in the identification and evaluation of brain tumors. Different types of brain tumors can have vastly different prognoses and treatment options, and accurate classification is essential for developing personalized treatment plans. Traditional classification methods are invasive and can be associated with significant risks for the patient. Deep learning-based classification methods can classify brain tumors based on their cellular characteristics using data, such as MRI images, reducing the need for invasive procedures and improving the accuracy and efficiency of tumor classification. The precise classification by a model can be evaluated using metrics like confusion matrix—which synthesizes the proficiency of a classification, and the performance metrics [20–22] like precision, recall, F1-score and support were calculated.

3.4 Models used

Several deep learning models have been used and compared to identify the best model for brain tumor segmentation and classification using MRI images. These models are trained on our dataset of MRI images and learnt to identify patterns and features that are characteristic of brain tumors. Different models have been evolved for different applications [23, 24, 24–26]. For segmentation, ResUNet [27], VGG19Unet [28], and U-Net [29] have been used.

ResUNet combines the residual connections of ResNet with the U-Net architecture, allowing the model to seize both regional and global information while reducing the vanishing gradient problem. VGG19Unet is a fusion of the VGG19 architecture and U-Net, where the features are inferred from the input image and use them for segmentation. U-Net is a fully convolutional neural network that uses an encoder–decoder architecture to segment the input image.

The U-Net model has been popularly used for medical image segmentation. It has a unique encoder–decoder architecture that can find both regional and global features of the input image. The encoder part of the network extracts attributes from the image, while the decoder part reconstructs the image at the output with pixel-level segmentation. The U-Net model is particularly well suited for brain tumor segmentation because it can handle the complexity and variability of the tumor’s shape and size. Its ability to produce accurate segmentations has made it a popular choice for medical image analysis. The U-Net architecture in deep learning used following relations of the model like convolutional, maxpooling layer and SoftMax activation function with equations as follows:

$$\text{output}_{\text{size}} = \frac{(\text{input}_{\text{size}} - \text{kernel}_{\text{size}} + 2 * \text{padding})}{\text{stride} + 1} \quad (4)$$

$$\text{output}_{\text{size}} = \frac{\text{input}_{\text{size}}}{\text{pool}_{\text{size}}} \quad (5)$$

$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum(\exp(z_j))} \text{ for } j = 1 \text{ to } K \quad (6)$$

Here Z is the input vector of the SoftMax activation function.

MobileNetV2 [30], VGG16 [31], and EfficientNetB3 [32] are all convolutional neural network [33, 34] models that can be used for brain tumor classification. MobileNetV2 is a lightweight CNN architecture that is optimized for mobile devices and has a small footprint. VGG16 is a popular CNN architecture that consists of 16 layers, with a deep and complex structure, making it more suitable for high-end computing devices. On the other hand, EfficientNetB3 is a relatively new CNN architecture that is known for its superior accuracy and computational efficiency.

EfficientNet B3 has gained popularity for its superior performance and efficiency in various fields. The model's efficiency comes from its use of a compound scaling method that optimizes the depth, width, and resolution of the network simultaneously. By leveraging the power of EfficientNet B3, it is possible to accurately and efficiently classify brain tumor images, which can have significant clinical implications for patient diagnosis and treatment. EfficientNet B3 is a complex neural network architecture which has compound scaling method which involves depth, width and resolution scaling, batch normalization and Swish activation function involved in its design and training using the following relations,

$$\text{Depth} = \alpha^\varphi \quad (7)$$

$$\text{Width} = \beta^\varphi \quad (8)$$

$$\text{Resolution} = \gamma^\varphi \quad (9)$$

where α , β , and γ gamma are scaling coefficients corresponding to depth, width and resolution decided by the user, φ is a scaling factor, which is a user defined parameter which determines the model size. Here, it is chosen as 1.2 and $\alpha^\varphi = 1.1$; if γ^φ is greater than 1, then downsample the input image resolution before applying to the next block. These equations are applied to each block of the network, and the overall architecture is a stack of these blocks with increasing depth, width, and resolution. The specific operations within each block, such as depth-wise convolutions and linear bottlenecks, contribute to the efficiency of the model.

$$y = \frac{(x - \text{mean})}{\sqrt{\text{variance} + \text{epsilon}}} * \text{gamma} + \text{beta} \quad (10)$$

Here x is the new value of a single component, gamma, and beta are learned per layer and y is the batch normalized output. And the Swish activation function is defined as:

$$f(x) = x * \frac{1}{(1 + e^{(\text{beta} * x)})} \quad (11)$$

It is obtained by multiplying input x by the sigmoidal activation function. Here 'beta' is the learnable parameter.

4 Experimental results and discussion

For our proposed work, the main programming languages used are Python and MATLAB. The platform used for this system is Jupyter, popular platform for deep learning that allows users to create and share interactive notebooks that combine code, visualizations, and text. Jupyter notebooks can be used with many deep learning frameworks, including TensorFlow, PyTorch, and Keras, and allow for easy experimentation and collaboration.

The MRI brain tumor dataset collected from Kaggle, which includes a total of 3929 images, is a valuable resource for developing and testing clinical image analysis deep learning models. The dataset comprises numerous MRI images of the brain that include various tumor types like glioma and meningioma. This dataset's extensive size allows the development of more advanced and accurate models capable of learning more sophisticated features while also enhancing their robustness. A sample dataset is shown in Fig. 2. The input images after preprocessing are first given to be segmented. Segmentation of brain tumors using deep learning is a promising approach to automate and enhance the accuracy of tumor delineation in medical imaging. Deep learning algorithms can analyze MRI scans to accurately identify and segment tumor regions, enabling better diagnosis and treatment planning for patients with brain tumors. Some of the popular models used and analyzed for this system are ResUnet, Vgg19Unet and Unet.

ResUnet is a deep learning architecture that combines residual connections with U-Net for improved accuracy in clinical image segmentation tasks such as brain tumor segmentation. It uses skip connections to preserve spatial information and enhance feature extraction. Figure 3 illustrates that an accuracy of 84% for the dataset was obtained and hence the next model Vgg19Unet is considered.

Vgg19Unet combines the VGG19 and U-Net models for improved accuracy in clinical image segmentation tasks such as brain tumor segmentation. It uses the pre-trained VGG19 for feature extraction and U-Net for pixel-level segmentation. For the dataset, it yielded an accuracy of 59% (see Fig. 4) which was comparatively less than ResUnet. Then U-Net architecture was used for segmentation. It uses a symmetric encoder–decoder structure with skip connections to preserve spatial information and

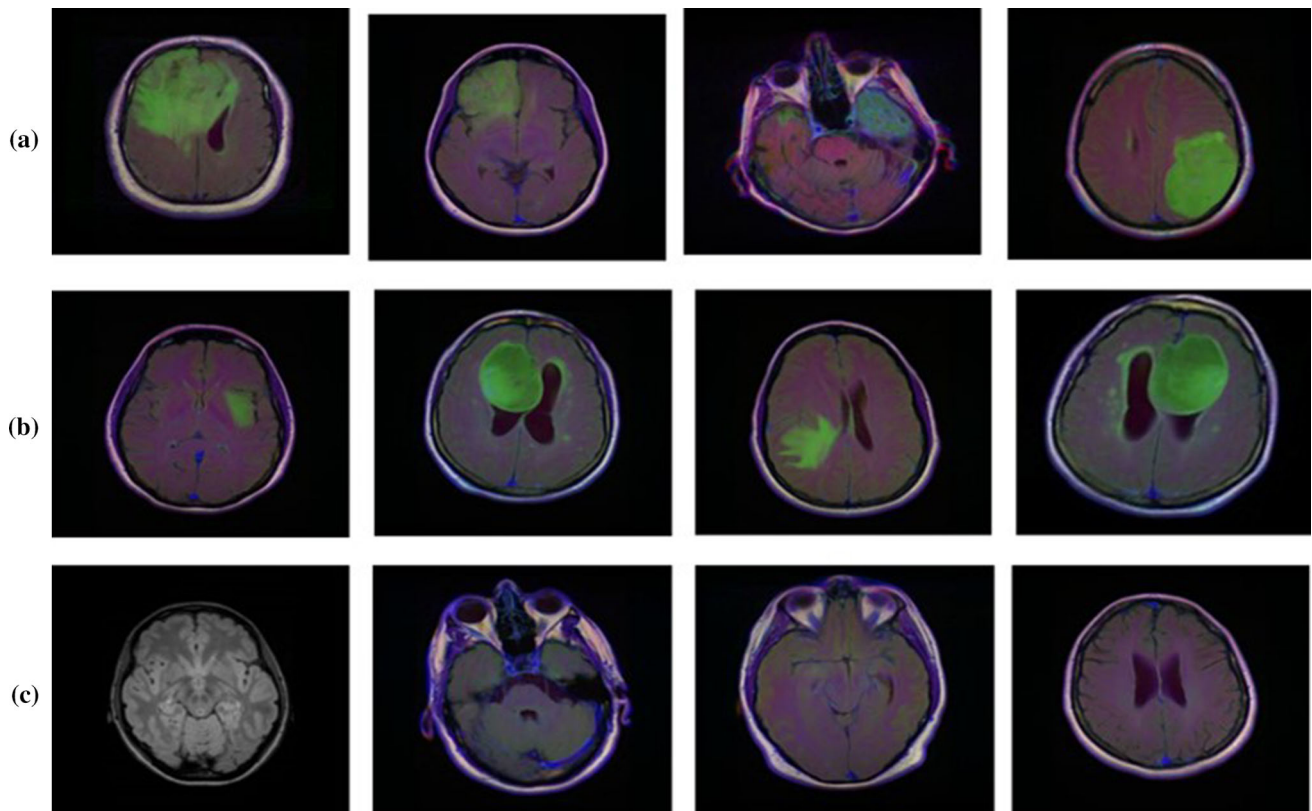


Fig. 2 Sample images of **a** meningioma, **b** glioma and **c** no tumor from dataset

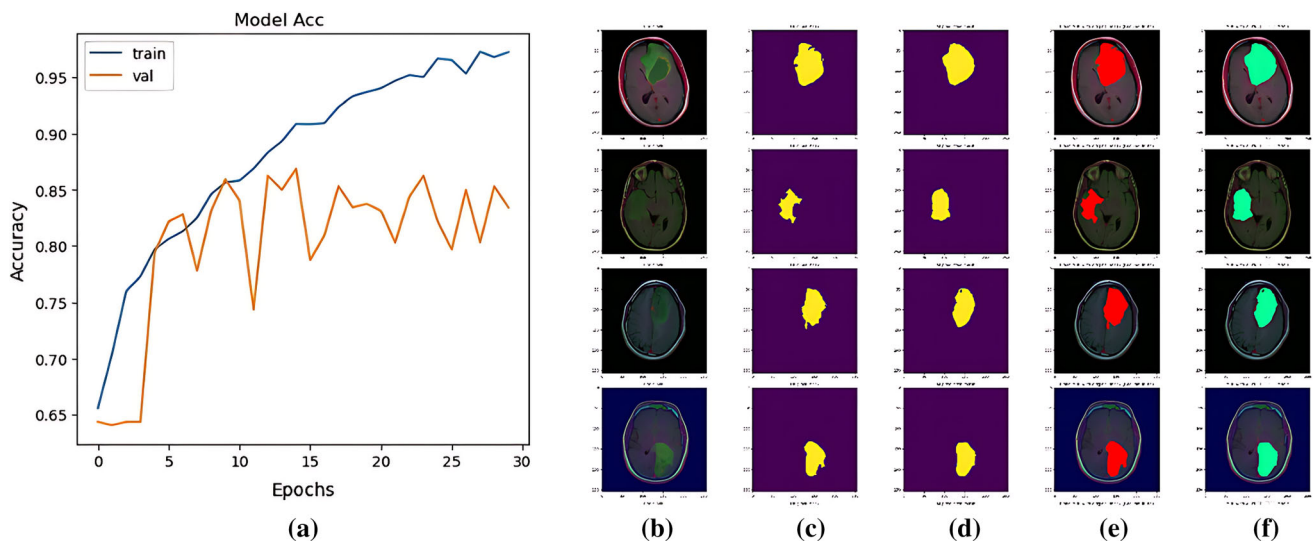


Fig. 3 ResUnet segmentation output **a** accuracy plot, **b** input images, **c** ground truth, **d** predicted value, **e** ground truth mask and **f** predicted value mask

enhance feature extraction, resulting in accurate pixel-level segmentation.

Figure 5 illustrates that an accuracy of 90% for the dataset was achieved and it is the highest among the compared models and provides better evaluation as given in Table 1. Hence, this model has been chosen as the best

suited model for segmentation. The overfitting issue predominantly present in VGG19 segmentation was reduced and manageable in U-Net as observed from Figs.3 and 4

The segmented output is then fed as input to the classification stage. Deep learning-based classification methods can categorize brain tumors based on their cellular

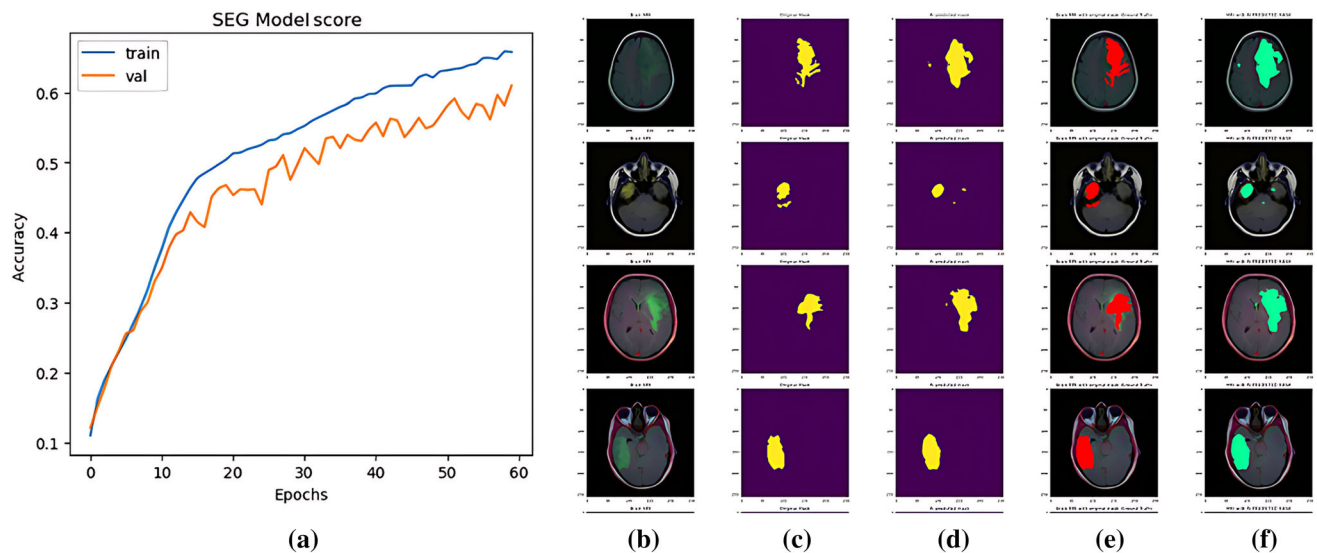


Fig. 4 Vgg19Unet segmentation output **a** accuracy plot, **b** input images, **c** ground truth, **d** predicted value, **e** ground truth mask, **f** predicted value mask

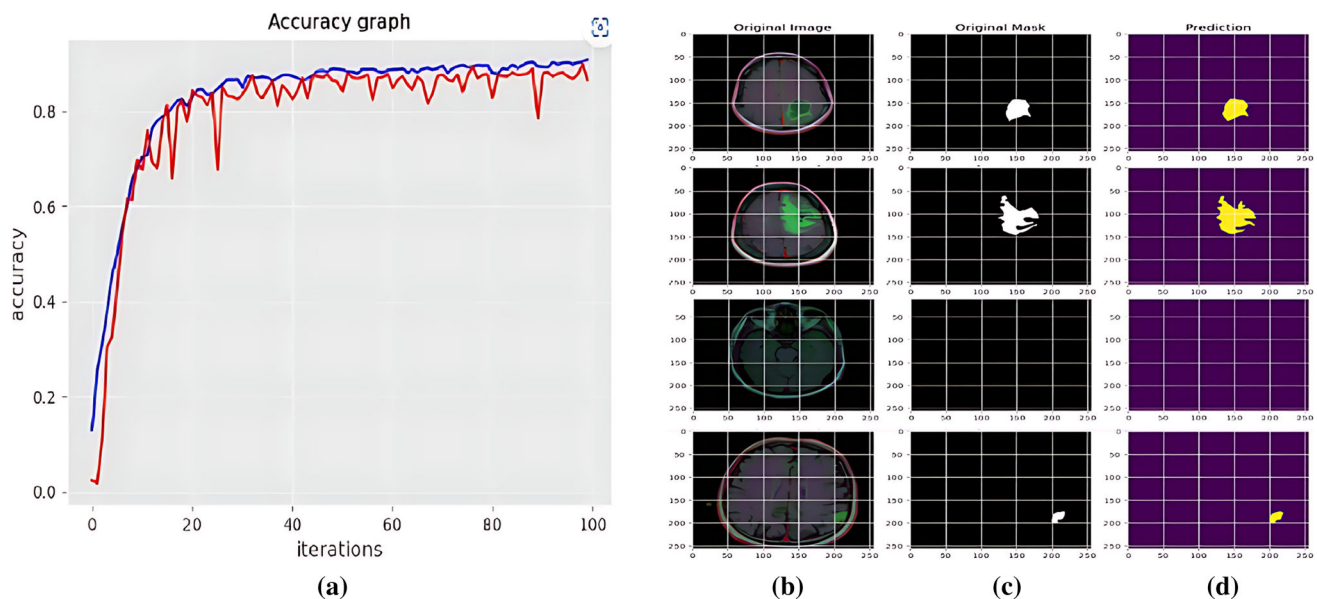


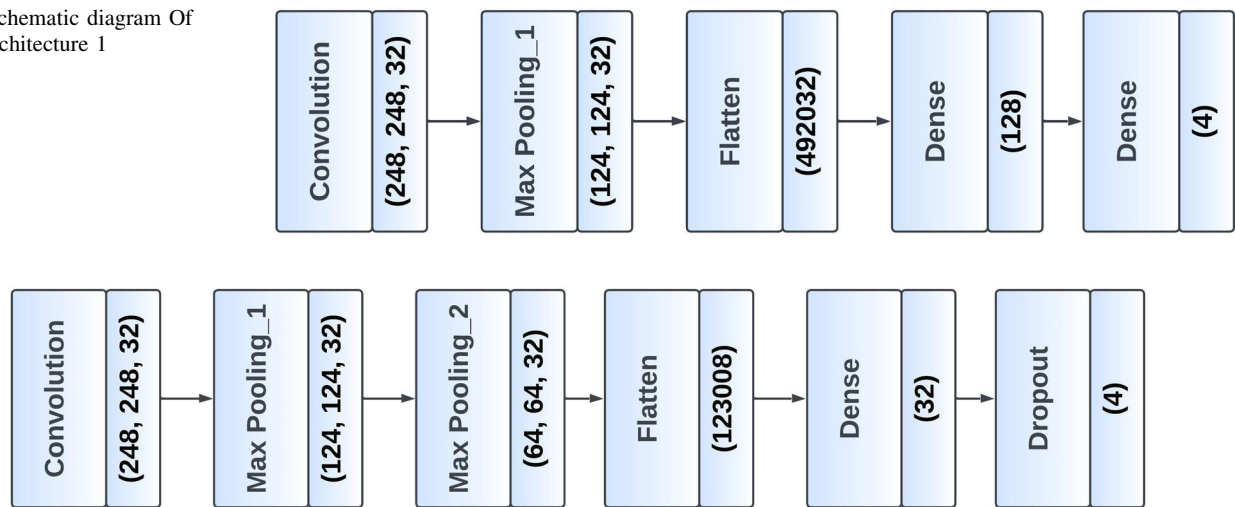
Fig. 5 U-Net segmentation output **a** accuracy plot, **b** input images, **c** ground truth, **d** predicted value

Table 1 Evaluation metrics and accuracies of the compared segmentation models

Model	Iou	Jaccard coefficient	Dice coefficient	Accuracy training%	Accuracy testing%
ResUnet	0.80	0.66	0.81	97	84
Vgg19Unet	0.83	0.709	0.82	67	59
Unet	0.99	0.98	0.80	93	90

characteristics using non-invasive imaging data, such as MRI images, reducing the need for invasive procedures and improving the accuracy and efficiency of tumor classification. Several popular models like CNN, Mobilenet-V2, Vgg16, and EfficientNetb3 are used and compared. CNNs

can learn features from medical images and classify tumors with high accuracy. They show promising results in differentiating between different models. The two CNN architecture from Keras are used as shown in Figs.6 and 7,

Fig. 6 Schematic diagram Of CNN Architecture 1**Fig. 7** Schematic diagram of CNN Architecture 2

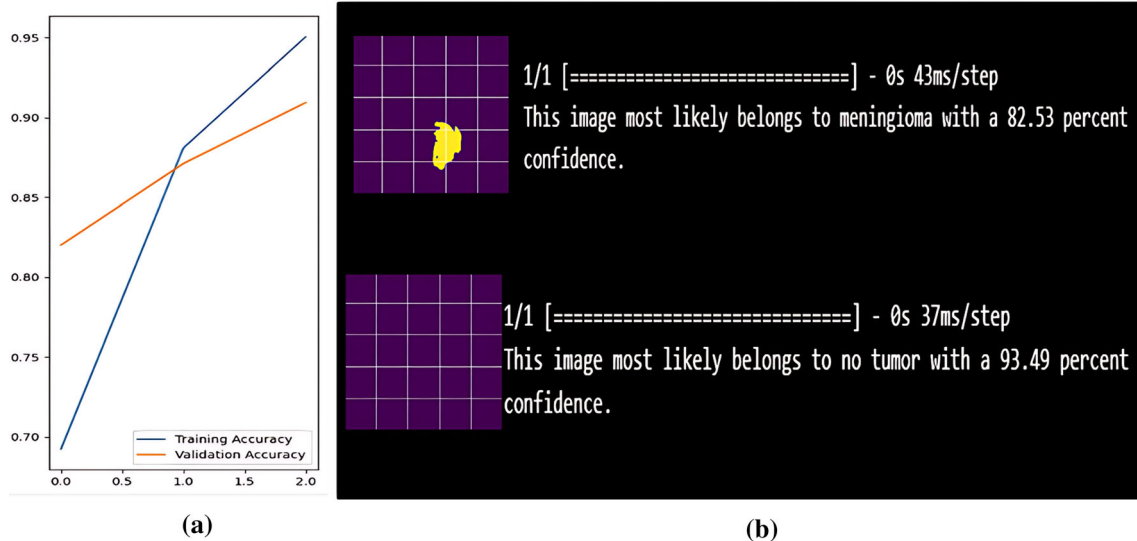
out of which the second architecture includes an additional maxpooling layer and a dropout layer.

For the given dataset, the CNN Architecture 1 yields an accuracy of 90% and CNN Architecture 2 yields an increased accuracy 94% due to its dropout layer (shown in Figs. 8 and 9). MobileNet V2 is a deep learning architecture that has been used for brain tumor classification tasks. Its lightweight design and low computational requirements make it suitable for diagnosis of brain tumors.

As depicted in Fig. 10, it yielded an accuracy of 84% which was less compared to CNN; hence to improve the results further, Vgg-16 was used. VGG16 is a popular deep learning model for image classification that has been successfully used for brain tumor classification. It has 16 layers, with a large number of trainable parameters, allowing it to learn intricate features from medical images.

Its effectiveness in brain tumor classification has been demonstrated in various studies. After testing the accuracy for the data as shown in Fig. 11, it fell to 84% compared to Mobilenet-V2. The next and final model considered for classification is EfficientNetb3. It is a state-of-the-art deep neural network architecture that has shown potential results for brain tumor classification tasks. It uses a combination of convolutional layers and feature fusion techniques to improve accuracy and efficiency. EfficientNet B3 can help improve early detection and diagnosis of brain tumors, leading to better patient outcomes.

This model yields the highest accuracy of 99% for testing and has precise values for evaluation metrics when compared with other models (refer Fig. 12). Figure 12a explains the graphical result of the best classification model ‘EfficientNet B3.’ This model was trained and tested for 40

**Fig. 8** CNN Architecture 1 classification model **a** accuracy plot and **b** results obtained

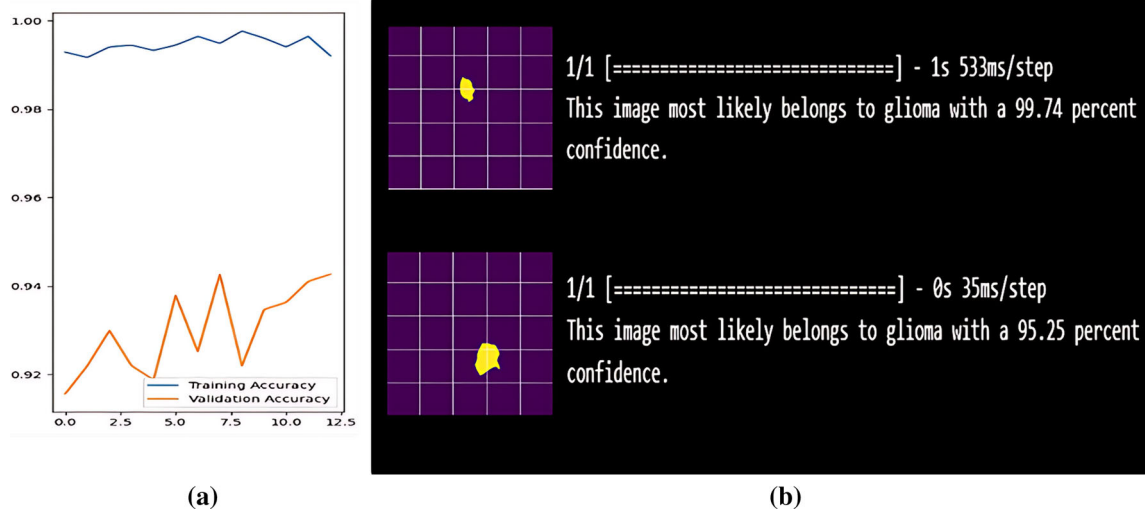


Fig. 9 CNN Architecture 2 classification model **a** accuracy plot and **b** results obtained

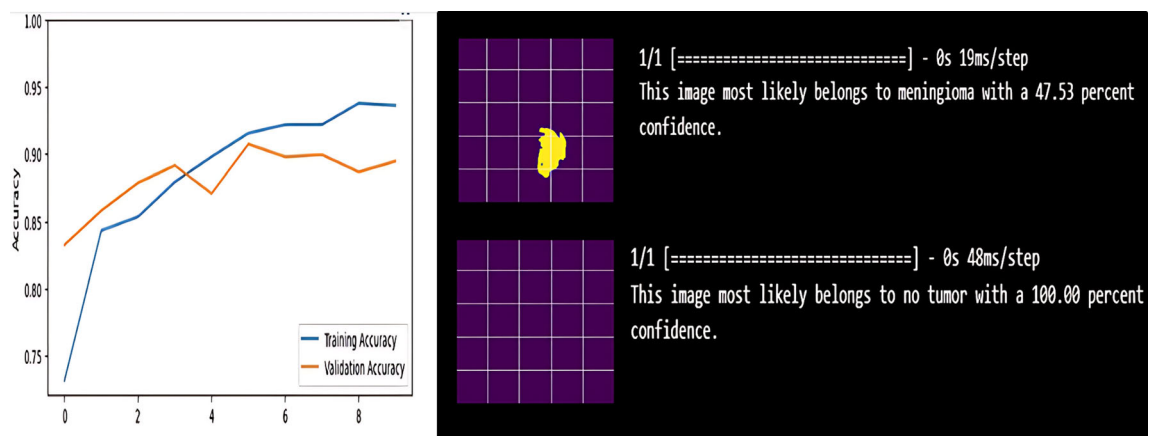


Fig. 10 MobileNet V2 classification model **a** accuracy plot and **b** results obtained

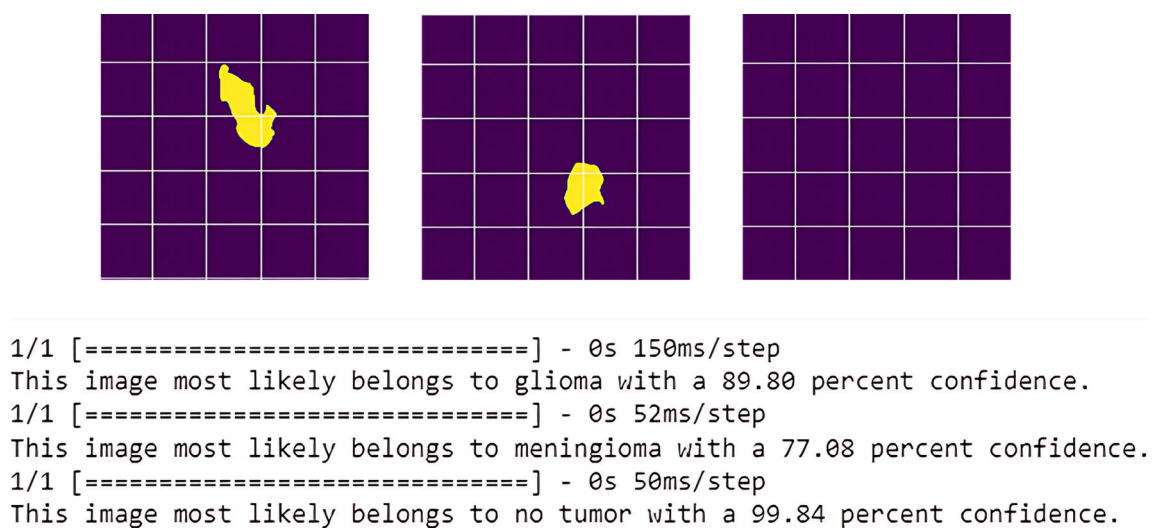


Fig. 11 VGG16 classification model results obtained

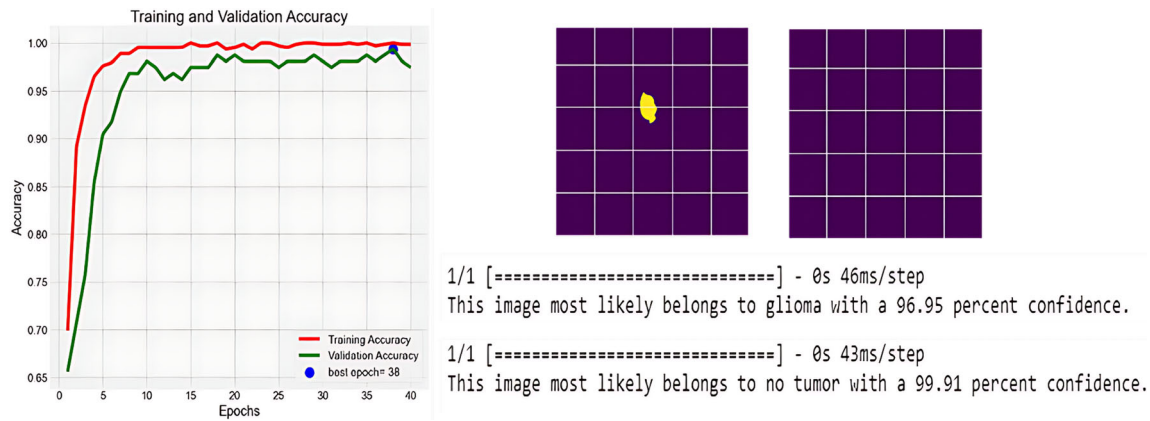


Fig. 12 EfficientNet B3 classification model **a** accuracy plot and **b** results obtained

epochs. The training accuracy obtained by this model was 100%, and the testing accuracy was 99%. Figure 12b explains the result obtained for the model 'EfficientNet B3.' Considering the first image in Fig. 12b, this shows the output predicted by the model for a glioma image given as input and returned the output as 'This image most likely belongs to glioma with a 96.95 percent confidence.' Similarly, the second image shows the output predicted by the model for a no-tumor image given as input and returns the output as 'This image most likely belongs to no tumor with a 99.91 percent confidence.' In the meantime, the overfitting observed in Figs. 8, 9, 10 and 11 is better handled with EfficientNet as observed from Fig. 12. Hence, this has been chosen as our final model for classification.

The intermediate layers in the UNet architecture provide a rich source of features for image analysis. The output of these layers can be used to extract various types of features, such as edges, shapes, and textures. These features can help in better understanding the image structure and assist in accurate segmentation. The intermediate layers can also be visualized to gain insights into the internal workings of the UNet as shown in Fig. 13. This model has been evaluated by observing the confusion matrix as shown in Table 2. Various classification models were analyzed by comparing the performance metrics and is shown in Table 3.

When comparing evaluation metrics of EfficientNetB3, VGG16, and MobileNet, EfficientNetB3 shows higher values in most cases. EfficientNetB3 shows higher precision, recall, and F1 score values, indicating better overall performance. Overall, EfficientNetB3 stands out as a powerful architecture that combines high accuracy with efficient resource usage.

Based on Fig. 14, we can observe that EfficientNetb3 is the most accurate model for both segmentation and classification tasks, with 99% accuracy for both training and testing and UNet shows higher accuracy in segmentation. On the other hand, ResUNet and MobileNet-V2 have high

accuracy on training but lower accuracy on testing. VGG16 yields more accuracy on training but comparatively less accuracy on testing. VGG19UNet has the lowest accuracy for both training and testing datasets.

Figure 15a showcases the results of segmentation models, including ResUNet, Vgg19UNet, and UNet. The physical mechanism underlying the different efficiencies of these networks is the different ways in which they are structured and trained. Since up to 10th epochs, there is no noticeable change, it is plotted from 10th epoch onwards. VGG16 is a relatively shallow network with a large number of parameters. This means that it is able to learn complex features from the data, but it is also relatively slow. The graph also shows that the accuracy of the U-Net model saturates after a certain number of epochs. This means that there is no significant benefit to training the model for more epochs after this point. This shows that the model has reached its limit in terms of its ability to learn from the data. This is because the model is only able to learn the statistical relationships between the features of the data and the presence of tumors. If the data are noisy or incomplete, then the model will not be able to learn these relationships perfectly. This will limit the accuracy of the model's predictions. In conclusion, the graph shows that the U-Net model can segment tumors more accurately with more training data. However, the accuracy of the model saturates after a certain number of epochs. This is because the model reaches its limit in terms of its ability to learn from the data.

Turning attention to Fig. 15b, which presents the results for classification models such as CNN Architecture 1, CNN Architecture 2, MobileNet V2, Vgg16, and EfficientNetB3, the graph shows that the accuracy of the U-Net model increases as the number of epochs trained increases. This is because the model is able to learn more about the data and improve its ability to classify tumors accurately as it is trained for more epochs, and it also learns about the

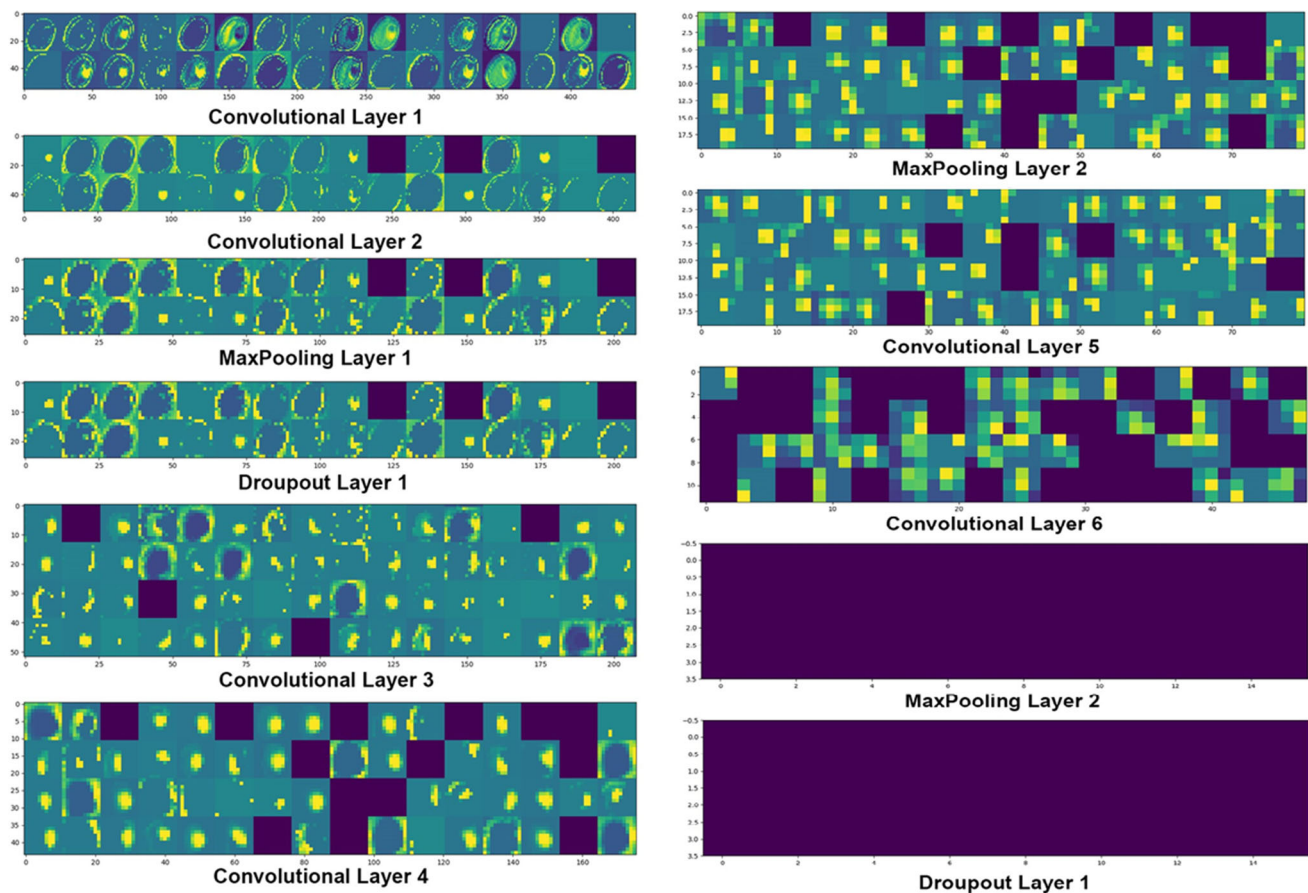


Fig. 13 Intermediate layer outputs of Unet

Table 2 Confusion matrix results for EfficientNetB3

	Glioma	Meningioma	No tumor
Glioma	133	0	0
Meningioma	2	144	0
No tumor	0	0	506

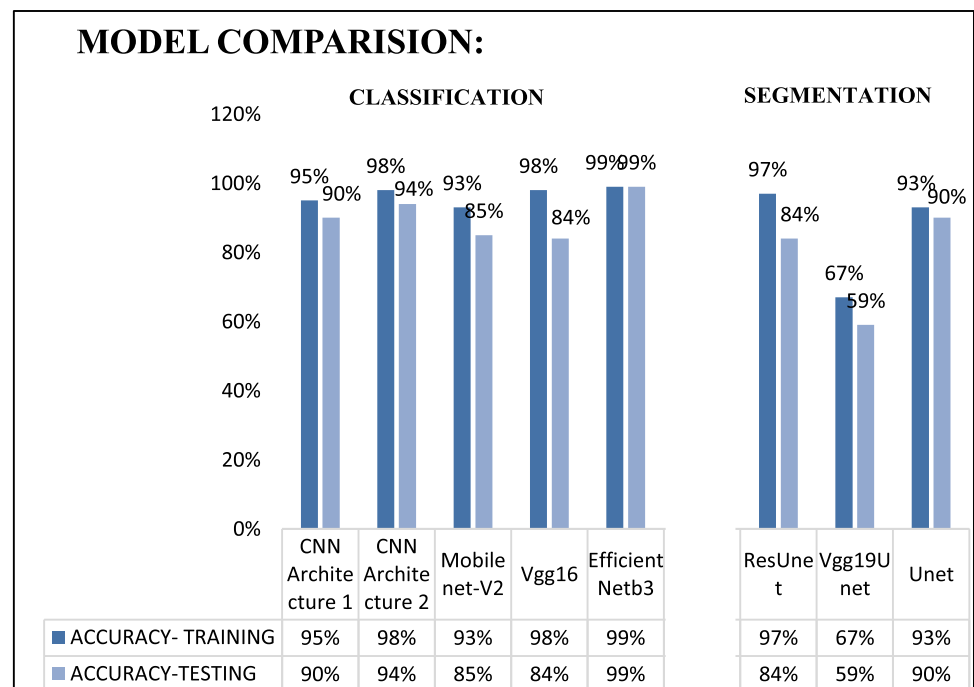
statistical relationships between the features of the data and the presence of tumors. For example, the model may learn that tumors tend to have higher signal intensity and a more irregular shape than healthy tissue. As the model is trained on more data, it is able to learn these relationships more accurately. MobileNet and EfficientNetB3 are both deeper networks with fewer parameters. This makes them faster than VGG16, but it also means that they are not able to learn complex features. EfficientNetB3 has a large number of layers and a large number of filters per layer. This allows EfficientNetB3 to learn complex patterns from the data, which is important for accurately classifying brain tumors and it uses compound scaling which scales up the width, depth and resolution proportionally. It has squeeze-and-

excitation (SE) modules. SE modules are a type of attention mechanism that allows the network to focus on the most important parts of the image. This can improve the network's accuracy, especially for small or difficult-to-see tumors. Overall, EfficientNetB3 is a powerful and efficient CNN architecture that is well suited for classifying MRI images of brain tumors.

The comparative analysis reveals that EfficientNet B3 emerged as the top performer with a test accuracy of 99%, followed by MobileNet at 85%, Vgg16 at 84%, CNN Architecture1 at 90%, and CNN Architecture 2 at 94%. The insights drawn from Fig. 15 lead us to identify 'Unet' as the optimal model for segmentation and 'EfficientNet B3' as the preferred choice for classification. Additionally, the algorithm was tested for the computation time. It is observed that lesser time (within 2–5 s) when compared with existing algorithms can be produced by using Lenovo 11th Gen Intel(R) Core™ i7-11800H @ 2.30 GHz, 2304 MHz, integrated GPU Intel(R) UHD Graphics. But, the same with Core i5 without GPU, it takes half an hour for loading the model and then 2–5 s to produce output after applying inputs.

Table 3 Evaluation metrics for classification models

Model	Type	Precision	Recall	F1 score	Support
CNN1	Glioma	0.68	0.32	0.46	133
	Meningioma	0.50	0.42	0.46	146
	No tumor	0.82	0.95	0.88	506
CNN2	Glioma	0.82	0.81	0.85	133
	Meningioma	0.85	0.87	0.80	146
	No tumor	0.90	0.90	0.90	506
Vgg16	Glioma	0.73	0.43	0.43	133
	Meningioma	0.52	0.34	0.34	146
	No tumor	0.83	0.95	0.95	506
MobilenetV2	Glioma	0.53	0.92	0.67	133
	Meningioma	0.72	0.99	0.16	146
	No tumor	0.93	0.98	0.95	506
Efficient NetB3	Glioma	1.00	0.98	0.99	133
	Meningioma	0.99	1.00	0.99	146
	No tumor	1.00	1.00	1.00	506

Fig. 14 Accuracy of the compared classification models and total epochs

4.1 Parameter estimation of tumor

In this section, it elaborates parameter estimation of brain tumors which involves the use of mathematical models to estimate various parameters related to the tumor's growth and characteristics. This information is important in diagnosis and treatment planning and can be obtained through various imaging techniques and computational methods. Accurate parameter estimation can aid in improving patient outcomes and developing better treatment strategies. This

is done with geometric and texture parameters and it is listed in Table 4.

Geometric parameters such as area, distance, major and minor axis of the tumor can provide important information about the tumor's growth and can be used to differentiate between tumor types and grade. From Table 5 while comparing the parameters, area provides information that clearly differentiates between meningioma and gliomas whereas the values of distance which refers to the measurement between two points in a tumor, major axis, the longest diameter of the tumor, and minor axis, the

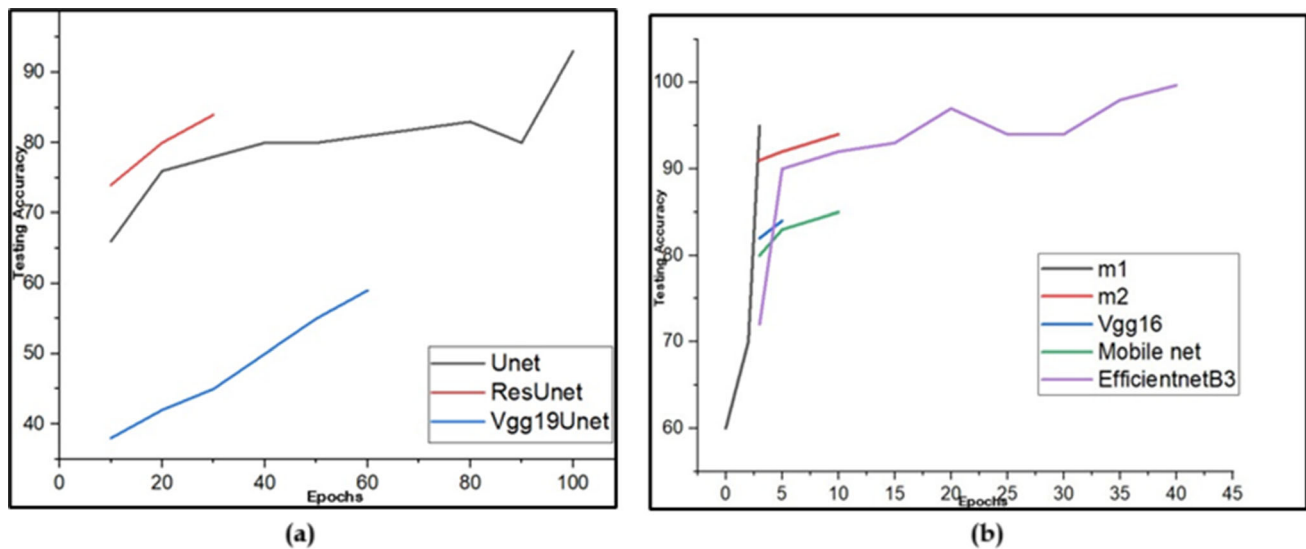


Fig. 15 Accuracy comparison plot for **a** segmentation models and **b** classification models

Table 4 Geometric and texture parameter analysis for glioma and meningioma brain tumor

	Area	Geometric parameters				Texture parameters		
		Major axis	Minor axis	distance	Contrast	Correlation	Energy	Homogeneity
G1	2646	68.7954	57.6882	63.5956	0.1231	0.9677	0.9197	0.9978
G2	1214	48.6421	33.2205	34.9679	0.0706	0.9606	0.9621	0.9987
G3	2079	55.3150	54.6274	57.2732	0.1261	0.9583	0.9358	0.9977
G4	2054	60.0339	50.1453	58.1753	0.1381	0.9538	0.9362	0.9975
G5	2722	70.0368	52.8912	30.6888	0.1171	0.9701	0.9177	0.9979
G8	1205	62.9361	25.8106	42.9959	0.1051	0.9408	0.9616	0.9981
G9	2107	84.2422	43.4940	57.0403	0.1681	0.9451	0.9341	0.9970
M1	3833	88.8601	57.4660	60.2291	0.1651	0.9695	0.8861	0.9971
M2	3086	72.4534	55.3856	38.4200	0.1141	0.9742	0.9076	0.9980
M3	5936	112.2523	70.0005	45.6120	0.1786	0.9779	0.8310	0.9968
M4	6189	110.9913	72.9139	43.8236	0.1756	0.9791	0.8248	0.9969
M5	1985	60.2046	43.6243	54.8791	0.0886	0.9693	0.9392	0.9984
M6	2904	69.0831	55.8497	54.9890	0.1021	0.9755	0.9129	0.9982
M7	1370	50.4627	35.1598	105.1336	0.0721	0.9642	0.9574	0.9987
M8	6542	100.0318	86.3244	44.8473	0.1711	0.9806	0.8162	0.9969
No tumor	0	0	0	44.8473	0	NAN	1	1

perpendicular diameter are not notable. Since the information is not significant, the texture parameters are considered. Texture parameters like contrast, correlation, energy and homogeneity were determined, which can help in identifying different types of tumors and can be used to differentiate. Contrast measures the difference in intensity between neighboring pixels, correlation measures their linear dependence, energy represents the sum of squared pixel values, and homogeneity measures the uniformity of intensity values. Among the parameters, the correlation value indicates that any value above 0.96 belongs to

meningioma and below to glioma. The parameters for no tumor were also achieved distinctly.

The experimental results have shown that both U-Net and EfficientNet B3 models can be effective in accurately segmenting and classifying brain tumors, which can be a significant step toward developing better diagnostic tools and treatment strategies for brain cancer patients. The experimental results have shown promising outcomes in terms of accuracy and efficiency. The U-Net model, which has been used for image segmentation tasks has demonstrated its effectiveness in segmenting brain tumors from MRI scans. On the other hand, the EfficientNet B3 model,

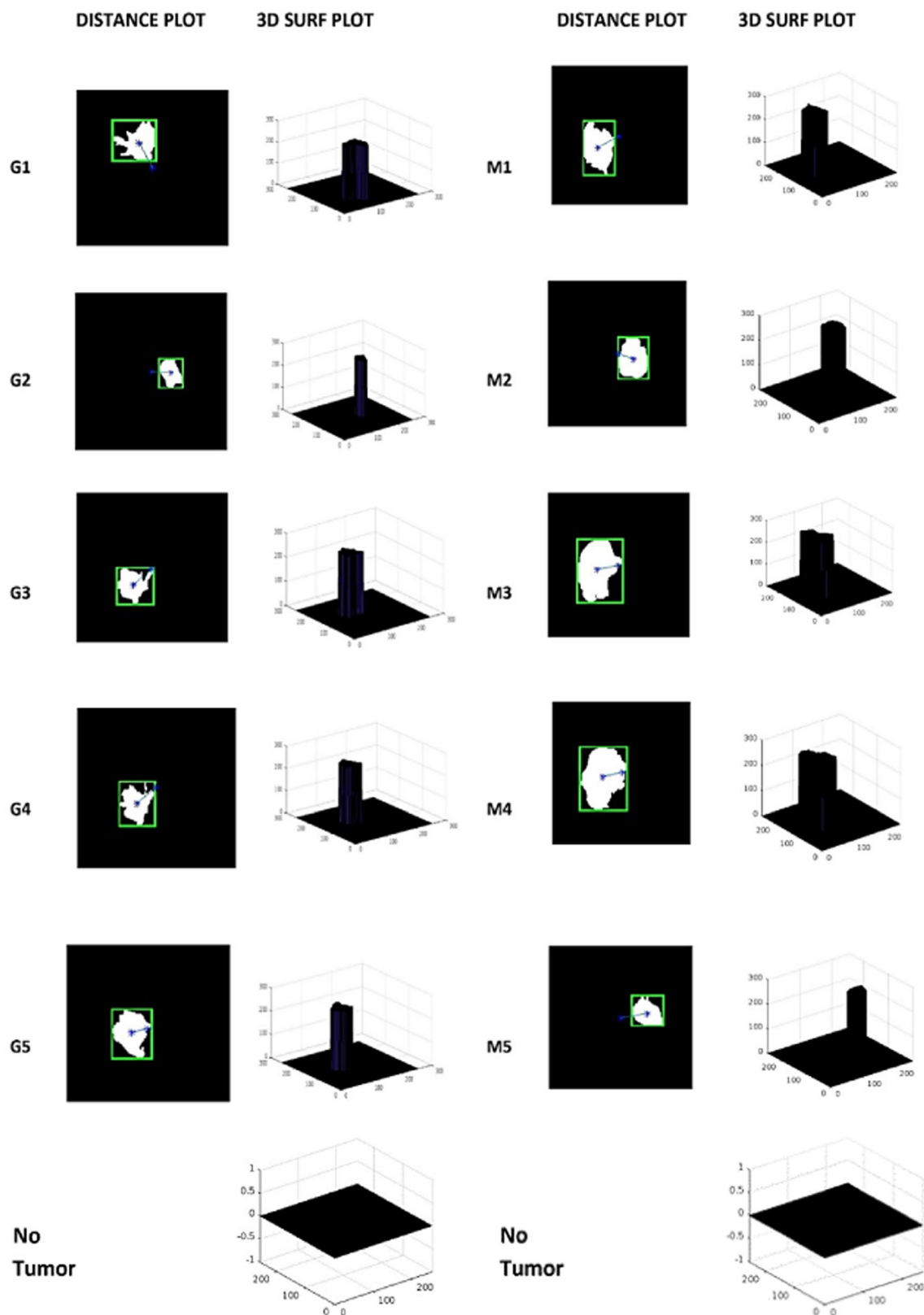
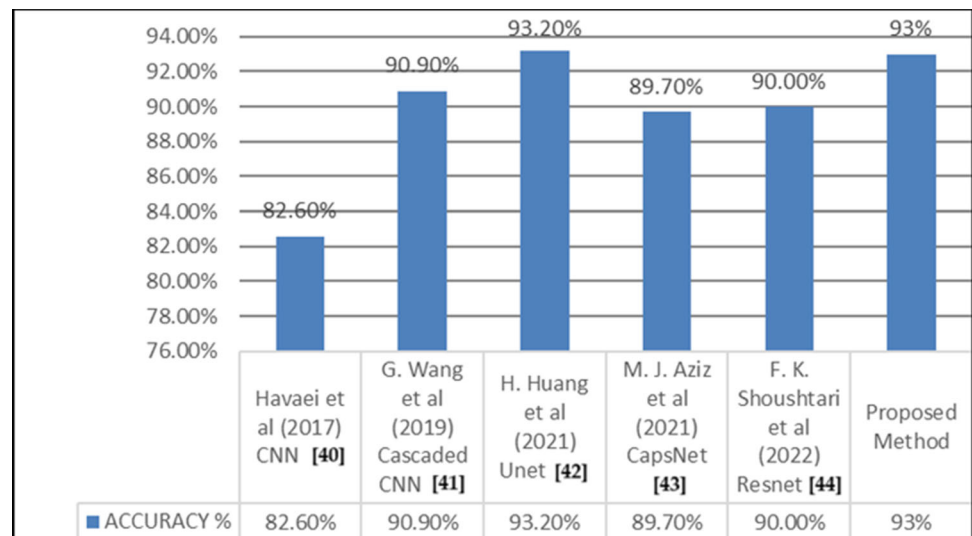
Table 5 Distance plot and 3d surf plot of meningiomas, gliomas and no tumor

Table 6 Significant works by other authors in classification of brain tumor

Author	Year	Methods	Accuracy (%)
Rao et al. [35]	2015	Enhanced Technique	67.0
Mohsen et al. [36]	2017	DWT	93.9
Saxena et al. [37]	2020	ResNet-50	95.0
Çinar& ildirim [38]	2021	Improved Model	97.0
Sushreeta Tripathy et al. [39]	2022	EfficientNet	99.0
Proposed Method	2023	EfficientNet B3	99.3

Fig. 16 Significant works by other authors in segmentation of brain tumor

which is a state-of-the-art deep learning model, has been utilized for image classification tasks and has shown high precision in detecting different classes of brain tumors.

Overall, the novel and accurate estimation of geometric and texture parameters in this system can help in the diagnosis, treatment planning, and monitoring of brain tumors, ultimately leading to improved patient outcomes.

4.2 Comparison with related work

Our proposed model was validated by comparing it with the previous work of other authors listed in Table 6 and Fig. 16 for the classification and region extraction of brain tumors. The tables compare and showcase the outcomes between our proposed approach and the existing approaches.

Some of the significant works done on the field of brain tumor classification are mentioned above in table where the highest accuracy is obtained by Sushreeta Tripathy et al. The family of efficient net is compared.

5 Conclusion

In conclusion, the proposed work presented a novel method for brain tumor segmentation and classification using U-Net and EfficientNet B3. The proposed approach achieved a high accuracy of 90% in tumor segmentation and comparatively better in classification tasks with an accuracy of 99.3%, outperforming some of the existing state-of-the-art methods providing a reliable and effective tool for diagnosis. The physical mechanism behind the graphical results is the activation of neurons in the model's convolutional layers. These neurons are designed to detect specific patterns and textures in the image, and their activation values correspond to the strength of those patterns. The model then uses these activation values to make a classification decision. In case of the glioma image, the model's neurons would be activated by the irregular shape and high signal intensity of the tumor. This would lead to a high activation value for the glioma class, which would result in the prediction 'This image most likely belongs to glioma with a 96.95 percent confidence.' In case of the no-tumor image, the model's neurons would not be activated by any specific patterns or textures. This would lead to a low activation value for all of the classes, which would

result in the prediction ‘This image most likely belongs to no tumor with a 99.91 percent confidence.’ U-Net’s large receptive field allows it to consider a wide range of contexts when making segmentation decisions, which helps to improve the accuracy of tumor detection. The U-Net model has a deep architecture, which allows it to extract high-level features from the input images. These high-level features are more likely to be associated with the presence of a tumor. The skip connections in the U-Net architecture allow the network to preserve spatial information during the downsampling process. This is important for accurate segmentation, as it allows the network to identify the precise location and boundaries of the tumor. The comparison of various models highlights the importance of selecting the appropriate architecture for specific tasks to achieve optimal results. The parameter estimation of tumor provides a different and unique approach that puts in light the different characteristics of tumor and helps in visualization of tumor for clinical purposes. Thus, the proposed framework accomplished the task in an exceptional manner. As the field continues to evolve, it is likely that deep learning-based approaches will become increasingly integrated into clinical practice, ultimately leading to better outcomes for patients with brain tumors.

Acknowledgements The authors express their gratitude to the Management and Principal of Mepco Schlenk Engineering College in Sivakasi for providing the necessary resources and support for conducting this research project.

Data availability The dataset used for this work is available in Kaggle dataset. The coding and the demonstration are available in the link: [https://github.com/BushkalaCP/Brain-tumor-segmentation-and-classification/blob/main/brain_seg_class\(final\).ipynb](https://github.com/BushkalaCP/Brain-tumor-segmentation-and-classification/blob/main/brain_seg_class(final).ipynb).

Declarations

Conflict of interest The authors do not have any conflicting interests to disclose that relate to the subject matter of this article.

References

- Ahmad S, Choudhury PK (2022) On the performance of deep transfer learning networks for brain tumor detection using MR images. *IEEE Access* 10:59099–59114
- Ali M, Gilani SO, Waris A, Zafar K, Jamil M (2020) Brain Tumour image segmentation using deep networks. *IEEE Access* 8:153589–153598
- Li M, Kuang L, Xu S, Sha Z (2019) Brain tumor detection based on multimodal information fusion and convolutional neural network. *IEEE Access* 7:180134–180146
- Pereira S, Pinto A, Alves V, Silva CA (2016) Brain Tumor segmentation using convolutional neural networks in MRI images. *IEEE Trans Med Imaging* 35(5):1240–1251
- Shah HA, Saeed F, Yun S, Park JH, Paul A, Kang JM (2022) A robust approach for brain tumor detection in magnetic resonance images using finetuned efficientNet. *IEEE Access* 10:65426–65438
- Pitchai R, Supraja P, Helen Victoria A, Madhavi M (2020) Brain tumor segmentation using deep learning and fuzzy K-means clustering for magnetic resonance images. *Neural Process Lett* 53:2519–2532
- Wang Y, Zu C, Hu G, Luo Y, Ma Z, He K, Wu X, Zhou J (2018) Automatic tumor segmentation with deep convolutional neural networks for radiotherapy applications. *Neural Process Lett* 48:1323–1334
- Sultan HH, Salem NM, Al-Atabany W (2019) Multi-classification of brain tumor images using deep neural network. *IEEE Access* 7:69215–69225
- Wang W, Li Y, Zou T, Wang X, You J, Luo Y (2020) A novel image classification approach via dense-mobilenet models. *Mob Inf Syst*. <https://doi.org/10.1155/2020/7602384>
- Vidhyarthi A, Agarwal R, Gupta D, Sharma R, Draheim D, Tiwari P (2022) Machine learning assisted methodology for multiclass classification of malignant brain tumors. *IEEE Access* 10:50624–50640
- Gumaei A, Hassan MM, Hassan MR, Alelaiwi A, Fortino G (2019) A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification. *IEEE Access* 7:36266–36273
- Ayadi W, Elhamzi W, Charfi I, Atri M (2021) Deep CNN for brain tumor classification. *Neural Process Lett* 53:671–700
- Ranjbarzadeh R, BagherianKasgari A, JafarzadehGhoushchi S et al (2021) Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. *Sci Rep* 11:10930. <https://doi.org/10.1038/s41598-021-90428-8>
- Liu Z, Tong L, Chen L et al (2023) Deep learning based brain tumor segmentation: a survey. *Complex Intell Syst* 9:1001–1026. <https://doi.org/10.1007/s40747-022-00815-5>
- FaysalAhamed Md, Munawar Hossain Md, Nahiduzzaman Md, Rabiul Islam Md, Robiul Islam Md, Ahsan M, Haider J (2023) A review on brain tumor segmentation based on deep learning methods with federated learning techniques. *Comput Med Imaging Graph* 10:102313
- Haq AU, Li JP, Khan S et al (2022) DACBT: deep learning approach for classification of brain tumors using MRI data in IoT healthcare environment. *Sci Rep* 12:15331. <https://doi.org/10.1038/s41598-022-19465-1>
- Díaz-Pernas FJ, Martínez-Zarzuela M, Antón-Rodríguez M, González-Ortega D (2021) A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network. *Healthcare (Basel)* 9(2):153. <https://doi.org/10.3390/healthcare9020153>. PMID:33540873;PMCID:PMC7912940
- Biratu ES, Schwenker F, Ayano YM, Debelee TG (2021) A survey of brain tumor segmentation and classification algorithms. *J Imaging* 7(9):179. <https://doi.org/10.3390/jimaging7090179>. PMID:34564105;PMCID:PMC8465364
- Aggarwal M, Tiwari AK, Sarathi M et al (2023) An early detection and segmentation of brain tumor using deep neural network. *BMC Med Inform Decis Mak* 23:78. <https://doi.org/10.1186/s12911-023-02174-8>
- Vijayakumari B, Kirubalini R, Manisha C (2020) Cadaver identification with dental radiographs using isoperimetric and nodal graph approach. *IET Biom* 9(1):38–45
- Vijayakumari B, Vidhya S, Saranya J (2023) Deep learning based gender classification with dental X-ray images. *Int J Biomed Eng Technol* 42(1):109–121
- Vijayakumari B, Vasanthal M, Dharshini SD (2023) Casualty Identification with Dental Radiographs and Photographs. *IETE J Res* 70(3):2929–2940

23. Ali B, Jubair S (2023) Rheological properties of Darcy-Forchheimer hybrid nanofluid flow with thermal emission and heat source over a curved slippery surface. *Pramana-J Phys* 97:127
24. Ali B, Jubair S, Al-Essa LA, Mahmood Z, Al-Bossly A, Alduais FS (2023) Boundary layer and heat transfer analysis of mixed convective nanofluid flow capturing the aspects of nanoparticles over a needle. *Mater Today Commun* 35:106253
25. Ali B, Jubair S (2022) Computing the steady state dynamics: the chemical graphs of complex reaction. *Innov J Math* 1:66–82
26. Arivazhagan S, Amrutha E, Jebarani WSL, Veena ST (2021) Hybrid convolutional neural network architecture driven by residual features for steganalysis of spatial steganographic algorithms. *Neural Comput Appl* 33:11465–11485
27. Lakshmanan B, Anand S (2021) Deep learning-based mitosis detection using genetic optimal feature set selection. *Int J Bio-Inspir Comput* 19(3):189–198
28. Zhang J, Jiang Z, Dong J, Hou Y, Liu B (2020) Attention gate ResU-Net for automatic MRI brain tumor segmentation. *IEEE Access* 8:58533–58545
29. Nguyen TH, Nguyen TN, Ngo BV (2022) A VGG-19 Model with transfer learning and image segmentation for classification of tomato leaf disease. *AgriEngineering* 4(4):871–887
30. Suri JS, Bhagawati M, Agarwal S, Paul S, Pandey A, Gupta SK, Saba L, Paraskevas KI, Khanna NN, Laird JR, Johri AM, Kalra MK, Fouda MM, Fatemi M, Naidu S (2023) Deep learning architecture for segmentation of vascular and non-vascular images: a microscopic look at UNet components buffered with pruning, explainable artificial intelligence, and Bias. *IEEE Access* 11:595–645
31. Pan H, Pang Z, Wang Y, Wang Y, Chen L (2020) A new image recognition and classification method combining transfer learning algorithm and MobileNet model for welding defects. *IEEE Access* 8:119951–119960
32. Yang H, Ni J, Gao J, Han Z, Luan T (2021) A novel method for peanut variety identification and classification by Improved VGG16. *Sci Rep* 11(1):15756
33. Alhichri H, Alswayed AS, Bazi Y, Ammour N, Alajlan NA (2021) Classification of remote sensing images using efficientnet-B3 CNN model with attention. *IEEE Access* 9:14078–14094
34. Huang Z et al (2020) Convolutional neural network based on complex networks for brain tumor image classification with a modified activation function. *IEEE Access* 8:89281–89290
35. Rao V, Shari Sarabi M, Jaiswal A (2015) Brain tumor segmentation with deep learning. *MICCAI Multimodal Brain Tumor Segm Chall (BraTS)* 59:1–4
36. Mohsen H, El-Dahshan E-S, El-Horbaty E-S, Salem A-B (2018) Classification using deep learning neural networks for brain tumors. *Future Comput Inform J* 3(1):68–71
37. Saxena P, Akshat M, Saumil M (2021) Predictive modeling of brain tumor: a deep learning approach. In: Sharma MK, Dhaka VS, Perumal T, Dey N, Tavares JMRS (eds) *Innovations in computational intelligence and computer vision*. Springer, Singapore, pp 275–285
38. Çınar A, Yildirim M (2020) Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. *Med Hypotheses* 139:109684
39. Tripathy S, Tripti S (2020) Unified preprocessing and enhancement technique for mammogram images. *Procedia Comput Sci* 167:285–292
40. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H (2017) Brain tumor segmentation with deep neural networks. *Med Image Anal* 35:18–31
41. Wang G, Li W, Ourselin S, Vercauteren T (2019) Automatic brain tumor segmentation based on cascaded convolutional neural networks with uncertainty estimation. *Front Comput Neurosci* 13:56
42. Huang H, Yang G, Zhang W, Xu X, Yang W, Jiang W, Lai X (2021) A Deep Multi-Task Learning Framework for Brain Tumor Segmentation. *Front Oncol* 11:690244
43. Aziz MJ, Zade AAT, Farnia P, Alimohamadi M, Makkiabadi B, Ahmadian A, and Alirezaie J (2021) Accurate Automatic Glioma Segmentation in Brain MRI images Based on CapsNet. In: *Proceedings of the annual international conference of the IEEE engineering in medicine and biology Society (EMBC)*
44. Shoushtari FK, Sina S, Dehkordi ANV (2022) Automatic segmentation of glioblastoma multiform brain tumor in MRI images: using Deeplabv3+ with pre-trained resnet18 weights. *Phys Med* 100:51–63

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.