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Hybrid depthwise convolution bottleneck in a Unet architecture for advanced brain tumor segmentation

Lahmar Hanine, Naimi Hilal *

Laboratoire de Modélisation Simulation et Optimization des Systèmes Complexes Réels, University of Djelfa, Djelfa 17000, Algeria

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ABSTRACT

Automated magnetic resonance imaging (MRI) segmentation plays an important role for the diagnosis and evaluation of brain tumors. However, it involves many challenges, including large variations in the shape and types of brain tumors, especially small ones that are difficult to diagnose early, and the complex border patterns that lead to missing data and low segmentation accuracy, putting specialists under time pressure. In this paper, we propose a new, lightweight network based on Unet by integrating skip connections with depthwise convolutional layers. This complementary technique allows us to improve the performance of the Unet model in explaining and analyzing medical images in a comprehensive and effective manner by transferring information from advanced layers to lower layers with greater quality. It helps avoid information loss and contributes to improving the network's ability to extract features better. Our suggested approach produced superior results compared to other Unet-like networks, as evidenced by the following metrics: accuracy of 99.82%, Intersection over union (IoU) of 83.34%, and Dice Similarity Coefficient (DSC) of 90.83%. Experimental findings demonstrated that the skip connections reconstructed in depthwise Convolution Bottleneck (DCB-Unet) integrated multi-scale contextual semantic information. In contrast to the majority of contemporary medical image segmentation models, our suggested approach more precisely recognizes organs, lesions, and segments.

1. Introduction

Brain tumor is a prevalent affliction affecting the brain, characterized by the uncontrolled and abnormal proliferation of brain cells (Zhao et al., 2024). It stands as one of the most perilous and life-threatening forms of cancer. Particularly in children and adolescents, this type of tumor is responsible for the highest number of cancer-related fatalities worldwide (Haleem et al., 2021). In order to identify the presence of a tumor, medical professionals specializing in radiology rely heavily on a range of medical imaging techniques (Cardoso et al., 2012). Among the various options available, magnetic resonance imaging (MRI) is the preferred choice for examining brain tumors due to its non-harmful nature. As part of their daily practice, radiologists manually detect brain tumors (Yang et al., 2018). Traditional segmentation methods in image processing have been widely studied and applied in many fields. These methods aim to divide digital images into multiple parts or regions based on specific characteristics. Some of the traditional segmentation techniques include: The standard technique for segmentation of MRI images of brain tumors is the threshold segmentation algorithm (Niu and Li, 2019). By identifying the intensity change in the image, the edge localization method finds the tumor edge pixels (Aslam et al., 2015). Neighboring pixels with similar properties are merged into a single region using the region expansion algorithm (Taghizadeh and Chalechale, 2022). Gray matter and cerebrospinal fluid have been successfully segmented in brain MRI images using a watershed segmentation approach in conjunction with an expectation–maximization algorithm (Prados et al., 2017). Although these methods are simple in design, they are time-consuming and error-prone. Since brain tumors are complex and patient-specific variations make manual segmentation of MRI images difficult, automatic segmentation is essential for appropriate diagnosis and treatment planning (Akter et al., 2024; Ullah et al., 2023). The field of image segmentation has evolved significantly due to deep learning-based segmentation techniques, where developing robust, accurate, and efficient solutions using deep learning techniques has become essential (Akter et al., 2024; Karimzadeh et al., 2021). Convolutional neural networks (CNN) are widely used in the field of brain tumor segmentation due to their remarkable image-processing capabilities (Akter et al., 2024). Unlike traditional methods, CNNs seamlessly integrate feature extraction and segmentation, eliminating the requirement for manually designed features. At present, the fully connected network (FCN) stands as the most efficient CNN model for the purpose of brain tumor segmentation (Behrad and Abadeh, 2022). By extracting the feature map from the last layer, the convolutional

* Corresponding author.
E-mail address: h.naimi@univ-djelfa.dz (N. Hilal).

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layer is able to reconstruct the initial image dimensions and estimate the dimensions of the output image. Ronneberger et al. (2015). The FCN model assigns a class to each pixel in the brain, enabling pixel-level tumor segmentation. Encryption and decryption are also performed by the FCN protocol, which serves as the basis for the robust Unet protocol (Akter et al., 2024). Unet combines features using a technique known as "channel dimension conjugation and merging" to create appropriate features (Akter et al., 2024). The Unet deep learning model was created specifically for medical image segmentation, especially in biomedical applications. In several competitions, including the 2015 ISBI Cell Tracking Challenge and the ISBI Neural Structures Segmentation Challenge in the ISBI Electron Microscopy Challenge, this method has been shown to perform better than previous methods (Ronneberger et al., 2015). Due to its ability to accurately segment images, the Unet model has found widespread application in medical imaging tasks. As a result, it is a valuable tool in the field of medical image analysis, especially in brain tumor segmentation. However, the Unet architecture faced some challenges related to feature fusion and spatial resolution. To improve the model's ability to handle small targets, simplify the feature extraction process, and improve the overall segmentation performance (Lu et al., 2022). We propose an improved version of the DCB-Unet that is built on the concept of the Unet model but has enhanced skip connections in the network. These connections are made possible by the incorporation of DepthwiseConv2D layers inside the bottleneck blocks (Koh et al., 2020), which improves the accuracy of image feature extraction. Depthwise convolution is necessary because applying channels-by-channels convolution significantly decreased the number of parameters compared with the traditional convolution, it kept the model simple while going deep. Using cogging functions instead of the traditional kinds of convolutions, we can perform the process of feature extraction, as well as optimize it and save such crucial information for improved results without losing on the invariability of the semantic angles. It enables the integration of semantic information of higher-order features with the low-level particulars of the features. This process adds improved semantic features and intricate characteristics to all features at all levels, resulting in improved segmentation results such as the segmentation of brain tumors which is crucial in medical applications. This work presents several significant contributions:

- Proposing a segmentation model for brain tumors in MRI images. This model utilizes the Unet-based DCB-Unet network architecture, incorporating Depthwise Convolution Bottleneck blocks into the skip links. The MRI images used in this study were obtained from the Cancer Imaging Archive (TCIA).
- Images from MRI sourced from Kaggle datasets were used to conduct experiments with high rigor to the proposed model.
- Evaluate the performance of the model by comparing it to previous works, using different performance metrics such as dice, IoU, and accuracy.

2. Related work

Deep learning models have revolutionized the development of semantic segmentation for brain tumors. Here, we mention some relevant articles from the past few years. Havaei et al. (2017) propose additional techniques for automatic brain tumor segmentation based on deep neural networks (DNN) to identify feature hierarchies that are specifically adapted to the brain tumor segmentation method and to integrate information between MRI methods. Therefore, a post-feature method based on connected components is specially designed to remove artificial regions in the obtained predictions. Chen et al. (2018) created a model called Dense Unet++ (DU++), which takes features from the Half Density Unit (HDU) and links them to the semantic level to create bridges, allowing the network to perform more accurate segmentation. This DU++ model aims to exploit convolution kernel size, optimization methods, and batch normalization techniques. Taking into account the SMCSRNet model designed by Ding et al. (2019) which outperforms most other classification methods in segmentation as well as in terms of time and computation saving, this model not only used connections as its main advantage but also used bridge connections for a robust and efficient network, for example. The message, contained in dense networks, was implicit to improve hierarchical information. Daimary et al. (2020) Discuss different types of CNN models, including Unet, SegNet, and ResNet18, specifically for brain tumor segmentation in MRI images. Karimzadeh et al. (2021) proposed a brain tumor segmentation method using a combination of attention and segmentation modules based on the Unet architecture. The attention module is designed to direct the deep network to focus more on regions containing tumors, while the segmentation module is responsible for performing detailed tumor segmentation. The attention module uses the expanded segmentation mask as the ground truth and introduces a new loss function to increase the true positive rate of tumor segmentation. These modules are integrated into the Unet architecture to improve the accuracy of brain tumor segmentation. Ru et al. (2021) devised the M-Unet model to segment brain tumors in MRI images. M-Unet improves on the original Unet model by adding multi-scale convolutional modules to better extract high-level and low-level features of tumor images, as well as avoid redundancy in the segmentation process. Moreover, a cosine learning rate attenuation algorithm is applied to achieve better network weights and prevent it from falling into local optimal solutions. Sharma et al. (2021) Implementing the Unet architecture with the classical framework as the basic building block of the segmentation system, transfer learning was used to address the issue of insufficient labeled data for brain tumor classification. and preprocessing techniques such as finite adaptive histogram equalization and normalization to enhance the diagnostic effectiveness of medical image analysis. Jena et al. (2023) He applied the variable depth technique embedded in the unet architecture based on the 2017 and 2019 BraTS datasets for semantic segmentation of brain tumors. The method involves replacing convolutional layers with layers of a different type, which may improve network performance along with reducing computational complexity. Pavithra et al. (2023) Proposed the development of Deep Neural Network (DNN) analysis based on modified Unet architecture for brain tumor segmentation in MRI images. This technique involves a two-step preprocessing phase aimed at improving the input images, followed by segmentation using unet-based designs. The necessity of addressing the low resolution of tumor tissue in T1 images leads to the combination of Flair, T2, and T1ce sequence types for tumor localization. The DNN model undergoes training using soft dice scaling as the cost function and the Adam optimization technique for parameter estimation. Akter et al. (2024) used deep learning techniques to classify and segment brain tumors. It uses data augmentation, and preprocessing techniques such as resizing, zooming, mode filter, Sobel filter, masking, and grayscale, as well as transfer learning models for classification. In addition, the segmentation model is used to segment brain tumors. Xu et al. (2024) used the segmentation methodology used in brain tumors and robust inference with Swin-T model to obtain global and local features from multimodal inputs. This is based on the hierarchical concept in Swin-T to find the best possible segmentation results while balancing the number of parameters and Flottante operations or FLOPs. The evaluation is performed using two datasets referred to as BraTS2020 and BraTS2021. For Aboussaleh et al. (2024), they used an improved U-Net architecture called Inception-UDet, which includes an Inception block to enhance brain tumor segmentation. This approach includes preprocessing, data augmentation, and four-way cross-validation to evaluate performance on the BraTS dataset. The most important points of the previously mentioned techniques are summarized in Table 1.

Table 1
Displaying previous works in last years.

Name	Year	Dataset	Model architecture	DSC or Iou
Havaei et al	2017	BRATS2012 BRATS2013	InputCascadeCNN	DSC (81%) DSC (84%)
Chen et al	2018	BRATS2015	improved network structure DU++	DSC (84.9%)
Ding et al	2019	BRATS2015	SMCSRNet	DSC (83.1%)
Daimary et al	2020	BraTS	Seg-Unet	IoU(73.4%)
Karimzadeh et al	2021	BraTS	AbUNet	DSC (79%±12%)
Ru et al	2021	MRI image	M-Unet	DSC(87.3%)
Sharma et al	2022	CE-MRI	transfer learning technique with Unet	DSC (87.71%) IoU (78.29%)
Jena et al	2023	BRATS2017	Depth reduced Unet	DSC (89%)
Pavithra et al	2023	MRI images	DNN	DSC (88.30%) IoU (79.20%)
Akter et al	2024	MRI images	Proposed model based on Unet	DSC (89%) IoU (81%)
Xu et al	2024	BRATS2020 BRATS2021	The BHN integrates the Swin converter with the Dual Path Feature Reasoning (DPFR) module	DSC (89.1%)
aboussaleh et al	2024	BRATS2020 BRATS2018 BRATS2017	Inception-UDet	DSC (87.9%) DSC (85.5%) DSC (83.9%)

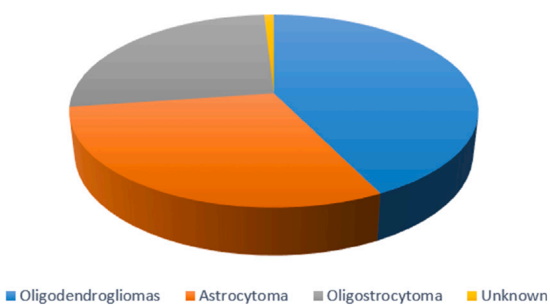


Fig. 1. Types of tumors and representation.

3. Material and methodology

3.1. Dataset

In this research, the FLAIR MRI LGG (low grade glioma) dataset was utilized, which was gathered from the open source site (Buda et al., 2019). The data set was captured from 110 patients, belonging to five healthcare organizations in total. The dataset provides all the components that can help analyze it. All the data has disparate tumor types, such as 47 of the oligodendrogliomas, 33 of the astrocytes, and 29 of the oliogastrocytomas. One sample is unknown. In addition to this, the dataset possesses 51 classified grade-2 tumors, 58 classified grade-3 tumors, and just one unknown grade tumor, as shown in Fig. 1. All FLAIR images in the set are reviewed as 2-dimensional and, as such, have dimensions of $256 \times 256 \times 3$. A total of 3929 images were divided from the collected dataset is split into train (2750 images), validation (786 images), and test (393 images) sets, the dataset contains the masks of the particular structure for each image. The images in Fig. 2 not only include the original images but also the corresponding mask (Kumar et al., 2023).

3.2. Data augmentation

The goal of image augmentation is to generalize our dataset by partaking of an existing dataset. The transformation techniques, such as various transformation techniques, are applied and employed on the original images to create a data set that is larger than our original image. Although this might seem like a straightforward task in theories, diversity in augmented images is indeed not an easy task to handle in real life. The alterations related to augmentation involve image rotation, vertical and horizontal displacement, and vertical and horizontal shearing. These changes provide the possibility of the adoption of different degrees of modifications in Fig. 3 (Garcea et al., 2023).

3.3. Methodology

In our research experiment, we worked on the FLAIR MRI dataset from Kaggle, which was already available free and open source. Firstly, we resized the pixel of inputs to 256 * 256 pixels in our proposed approach Fig. 4. The set of already-gained images was divided into two subsets: validation and training sets. Our proposed model, DCB-Unet, is trained using an image model on the training set images Medical. This neural network takes the form of two units, the unet branch network and one bottleneck block that has a fair relationship with the work of cipher and decoder components Fig. 5. which is functionally linked to the encryption and decoder units. The encoder focuses on high-level features of the input images that are later used by the decoder for the segmentation task, while depthwise convolution bottleneck filters help the system retain information about spatial transitions between inputs and outputs while improving their quality. The trained model is fed with verification sample images to examine its results and output accuracy, and then we test it on the previously held-out dataset. The DCB-Unet model can create a segmentation mask for each of the images provided as input. To prove the accuracy and efficiency of the proposed DCB-Unet model, we calculated performance metrics on the mask Origin and predicted mask, such as dice coefficient, accuracy, IoU, etc.

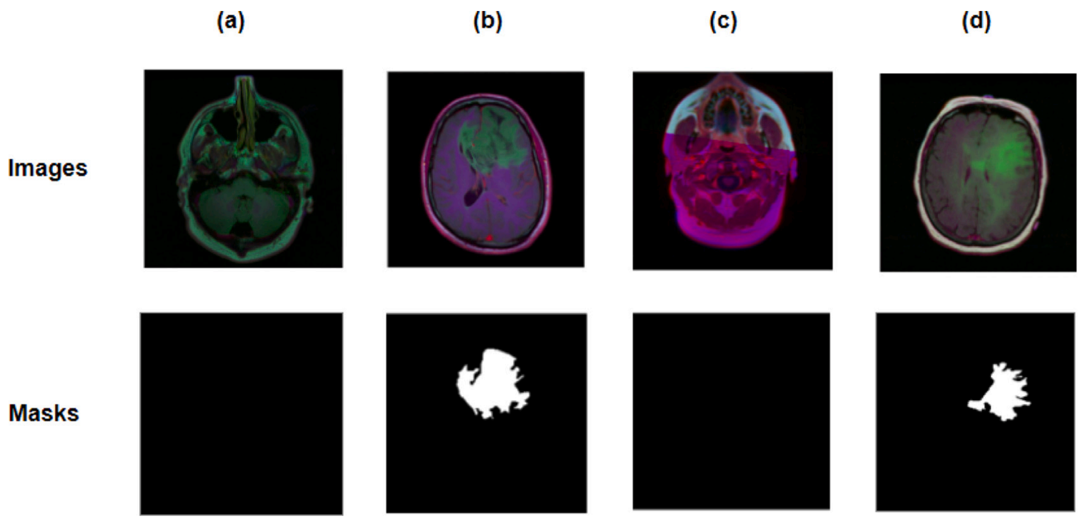


Fig. 2. FLAIR MRI images: Original image without tumor and with tumor, ground truth image without tumor and with tumor.

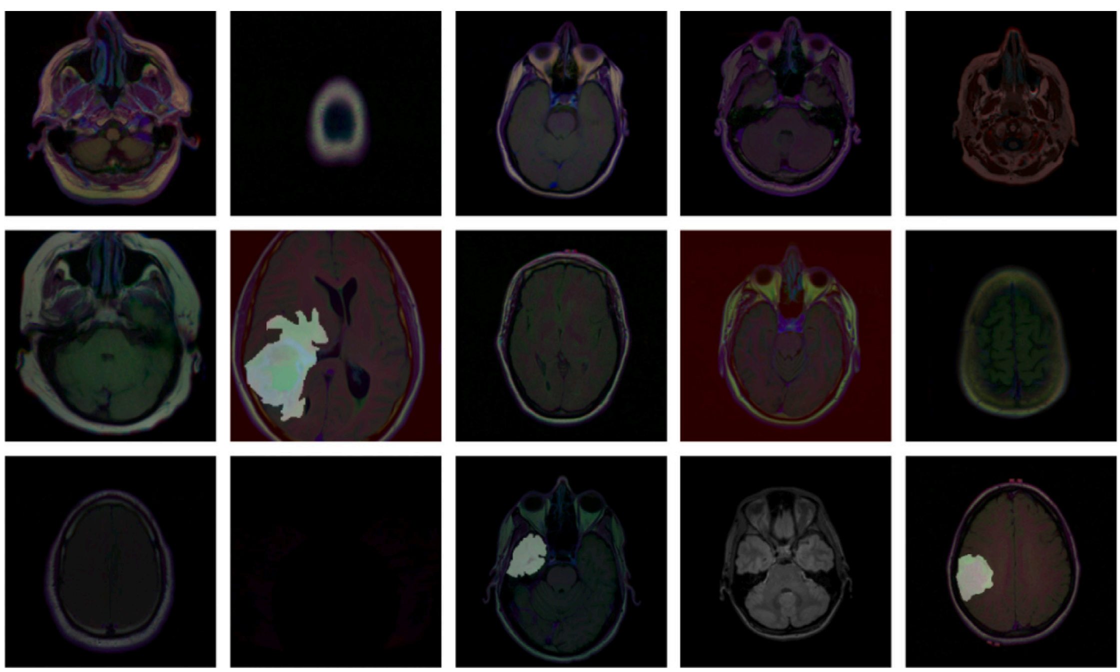


Fig. 3. FLAIR MRI images after preprocessing.

3.4. Proposed DCB-Unet model

We created the DCB-Unet model Fig. 6 based on the Unet architecture by incorporating depthwise convolution bottleneck blocks into the skip connections of the network to increase the depth of the model based on the properties of depthwise convolutions. To reduce the number of parameters and computations, so that the network is more efficient, regular convolutions with filters are deployed across all channels. but depthwise convolutions are preceded by different channels independently to ensure that information is not lost and is further optimized for use in semantic segmentation. We set four depthwise convolution bottleneck blocks to perform the feature extraction process by passing higher-level spatial features to lower-level features from the input block to the output block while keeping the same number of filters in the input and output of each connection line to overcome the obstacles of dealing with small goals without losing them. Finally, we get an output image which is a binary segmentation map, where pixel class refers to the distinction between pixels in the image based on previously extracted features, elements, and regions that can be assigned to a wider scope and precise definition with very detailed spatial expression to obtain a wise classification for each pixel and thus high accuracy and efficiency for semantic segmentation.

3.5. Quality metrics

In order to evaluate the accuracy and efficiency of our modified model and compare it with other models, we relied in this study on several measures, including dice, IoU, and accuracy, which we will discuss in this section.

3.5.1. Dice criterion

The dice criterion is an approach that can be employed to assess the precision of segmentation, and it is calculated utilizing the subsequent equation (Larbi et al., 2023):

$$Dice = \frac{2TP}{2TP + FP + FN} \tag{1}$$

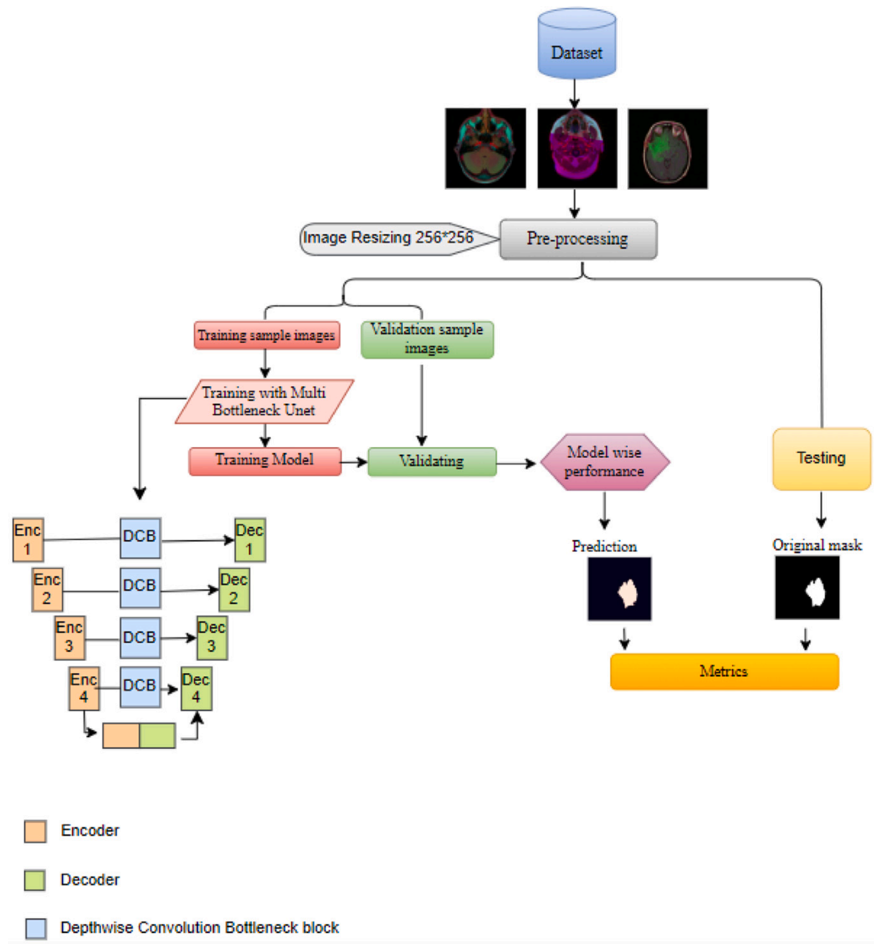


Fig. 4. Block diagram of the approach that was proposed.

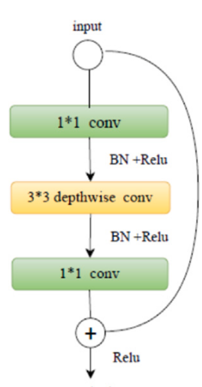


Fig. 5. Depthwise convolution bottleneck.

3.5.2. Accuracy

The accuracy of diagnosing or discriminating a particular condition using the binary segmentation approach is the performance appraisal (Larbi et al., 2023):

$$accuracy = \frac{TP + TN}{FP + FN + TP + TN} \tag{2}$$

3.5.3. IoUscore

The iou principle evaluates the prediction performance of the network through the method of evaluating the overlap level between the ground truth and the prediction, and it is calculated utilizing this equation (Huang et al., 2019):

$$IoU = \frac{TP}{TP + FP + FN} \tag{3}$$

4. Experimental results and discussion

4.1. Results

The proposed model segments FLAIR MRI images collected from 110 patients and performs accurate discrimination between the tumor and the surrounding healthy brain tissue. Fig. 7 shows the success of training and testing during the training duration of the model. Both quality metrics, such as dice and the IoU coefficient for training and testing, increase almost simultaneously, indicating that the model does not suffer from overfitting.

According to the results obtained from the evaluation criteria, the tumor location was determined for the test data with perfect accuracy using FLAIR MRI images. Fig. 8 shows several sample images of the real and predicted tumor area using the proposed DCB-Unet model based on the test results that showed great similarity between the areas real and predicted tumors, which means that the DCB-Unet model is well suited to the RGB data set. It also performed very well in identifying tumor tissues and segmenting them from healthy brain tissues.

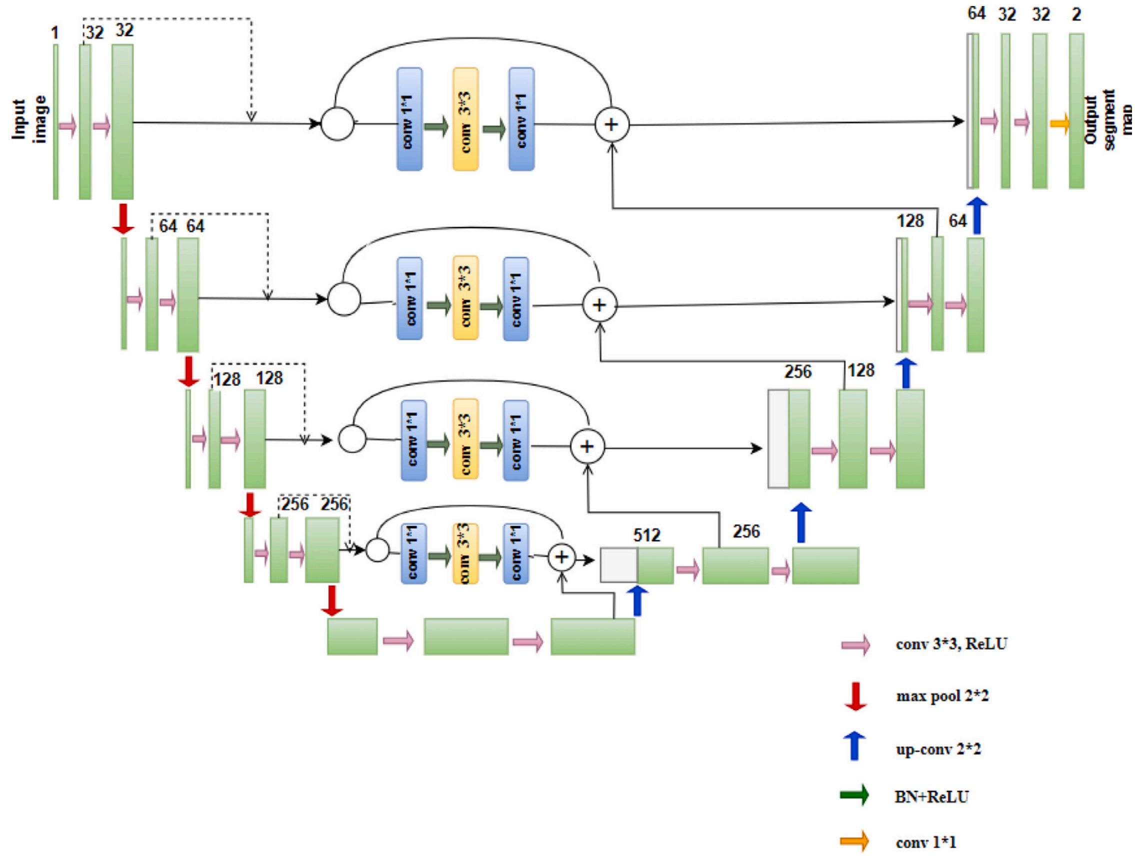


Fig. 6. Proposed DCB-Unet model.

Table 2
Displaying previous works in last years.

Parameters	Train	valid	test
Accuracy	0.9985	0.9981	0.9982
Dice	0.9286	0.913	0.9083
IoU	0.8673	0.8409	0.8334

The proposed strategy produced promising results Table 2 and Fig. 9 in which we relied on the integration of depthwise convolution bottleneck blocks into the network bypass connections to enhance feature transfer and keep them from being lost from the encryption unit to the decryption unit.

The model was trained, validated, and then tested. The test data set indicates that the DCB-Unet model can predict the tumor in MRI images and its segmentation with a dice value of about 0.90 and a dice loss of 0.10, as well as successfully distinguish between pixels that were positive in the tumor reality and those that were false positives. It was found that the model successfully identified the majority of positive pixels with an accuracy of 0.99 and 0.83 for the IoU coefficient. We can see that the IoU coefficient performs well in both the training and validation datasets with a value above 50%, which means that the model makes a good prediction.

4.2. Comparison with previous works

Many contributions to medical image segmentation have been made by many researchers. Including Kumar et al. (2023) used the new ResUUnet model to perform multispectral segmentation of FLAIR images and obtained dice accuracy and IoU of 99.80%, 90.56%, and 82.93%, respectively, while Sathish et al. (2024) brain tumor segmentation was performed using a model called VGG-Unet, which integrates the weights of the initial model VGG16 in the encoder module with a stand-alone module in the decoder section to get 88.25% dice value and 87.73% IoU factor. As for Shomirov et al. (2022), they proposed modifying the 3D Unet segmentation model based on the local encoder with the generalized loss function (GL) that was trained by the Adam optimization algorithm in order to improve performance and obtained an accurate 97.24%, and the IoU coefficient is 51.57%. dish (Renugadevi et al., 2023)Advanced and popular methods for segmenting brain tumors by selecting the Unet++ architecture for recognition. The tumor obtained an accuracy of 98.81% and 74.83% for IoU during the testing phase. Deep learning and transfer learning are the methods adopted by Joshi and Singh (2024) in semantic segmentation.brain tumors based on the Unet network. Thus, they obtained an accuracy of 99.88% and 62.02%.37.55% for the dice coefficient and IoU coefficient, respectively. From Table 3 we note that although the specific methodologies and models used are different, they all rely on deep learning, especially convolutional neural networks (CNNs) for image segmentation, which is what our research was, as we relied on the Unet architecture for image segmentation to produce the proposed DCB-Unet model. All contributions indicate high segmentation accuracy rates, leading to its potential use in clinical applications such as computer-aided diagnosis, treatment planning, as well as monitoring disease progression. However, the outperformance of the proposed DCB-Unet model was clear, as we obtained a segmentation accuracy of 99.84%, as well as 90.83% and 83.34% for dice and IoU, respectively. This refers to the efficient strategy used by incorporating throttling blocks in network skip communications while preserving the encoder and decoder modules of the original network, the depthwise convolution the blocks, the model can efficiently capture complex spatial patterns and features in medical images and obtain accurate segmentation of the overlap between the predicted real regions and the

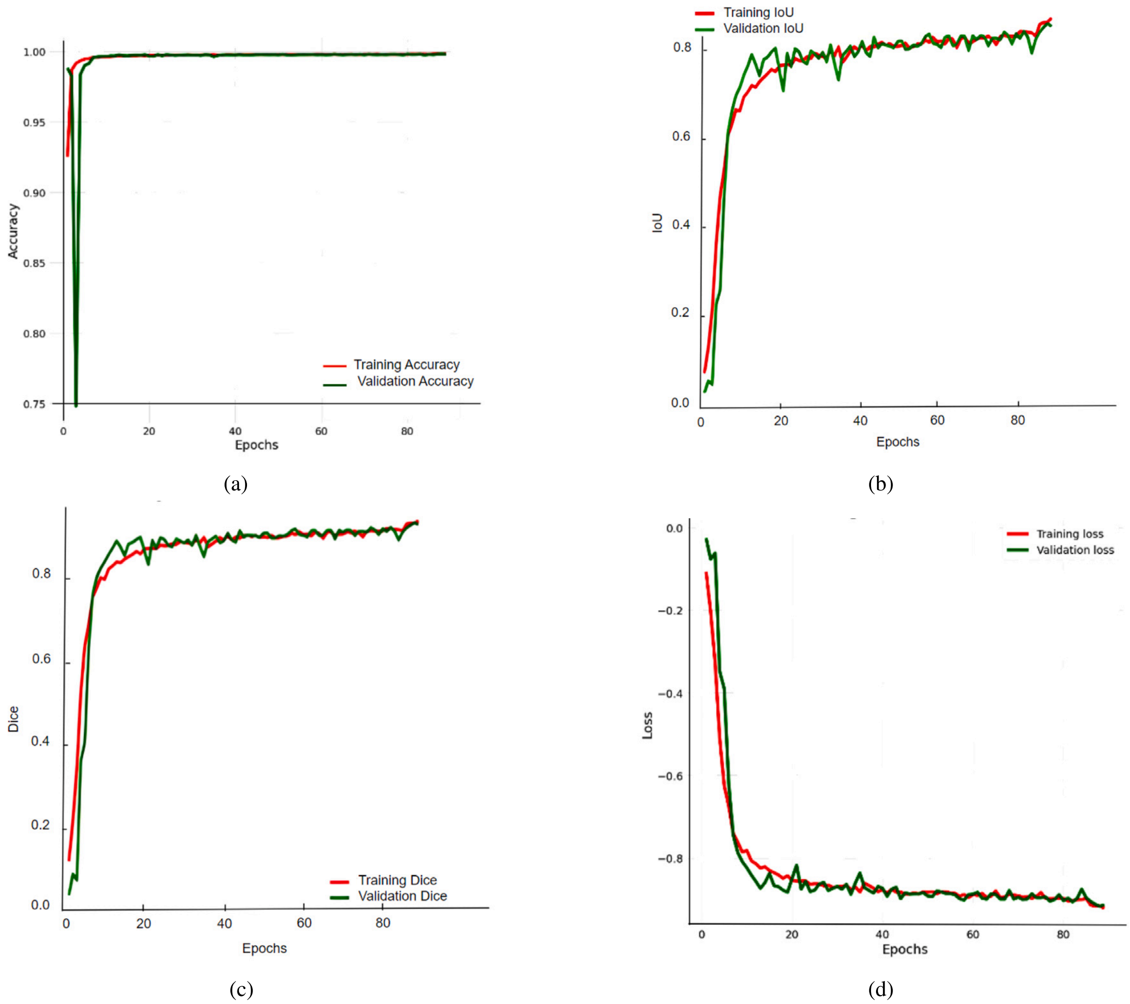


Fig. 7. (a) Accuracy plot for proposed model (b) IoU coefficient plot for proposed model (c) Dice coefficient plot for proposed model (d) Loss plot for proposed model.

Table 3
Comparison of the previous segmentation methodology with the proposed model.

References	Dataset	Methodologys	Accuracy	Dice	IoU	Loss
Kumar et al. (2023)	LGG data	The main technique used is the Resnet Backbone U-net model for segmentation of a brain tumor from flier MRI images	0.9980	0.9056	0.8293	−0.9013
Sathish et al. (2024)	EPISURG and clinical dataset in DICOM format	The proposed model and its name promote the interest of VGG-Unet, integrates VGG 16 initial weights in the Encryption section includes the self-attention module in the decoder	–	0.8825	0.8773	–
Shomirov et al. (2022)	BraTS 2020	A modified 3D Unet segmentation model based on the combined encoder (Unet AE) with generalized loss function (GDL) trained by the ADAM optimization algorithm was used to address the problem of class imbalance in brain tumor segmentation	0.9724	–	0.5157	–
Renugadevi et al. (2023)	BraTS 2020	Brain tumor segmentation using the Unet++ architecture	0.9881	–	0.7483	0.2517
Joshi and Singh (2024)	BraTS 2020	Modifications have been made to the design of the Unet Network, and the modified Unet	0.9938	0.6202	0.3755	0.0179
Proposed approach	LGG data	We have developed the Unet network by integrating depthwise convolution bottleneck blocks into the network's skip connections	**0.9984**	**0.9083**	**0.8334**	**−0.9084**

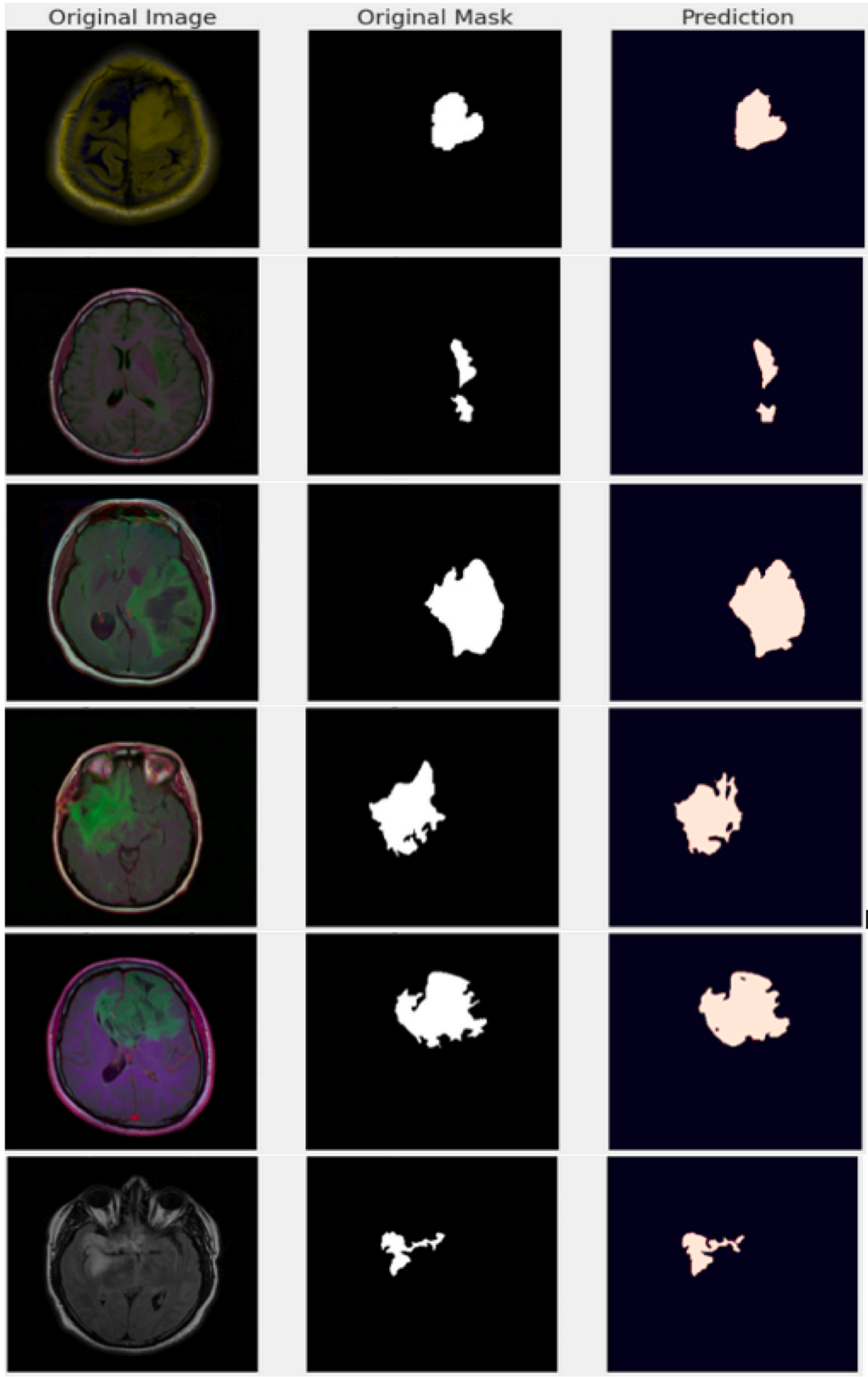


Fig. 8. Ground truth image and segmented image.

ground truth regions. which reduces the computational cost. Due to the depthwise convolution features in the blocks, the model can efficiently capture complex spatial patterns and features in medical images and obtain accurate segmentation of the overlap between the predicted real regions and the ground truth regions.

The performance evaluation of deep learning-based models depends not only on the final segmentation results but also on the performance of the model during the training and testing phases, as all previous models as well as our proposed model obtained high accuracy in image segmentation as mentioned earlier. We will focus our attention on the variation in the dice and IoU coefficients in Figs. 10 11 12 13 14.

Through the graphs of the dice and IoU coefficients represented in the table above, we notice that the previous models suffered from some disturbances during the training and validation period and a state of instability, which makes them prone to overfitting, both dice and IoU are similar in terms of the computational base, as they express the overlap between segmented and ground truth regions, which is important in brain tumor segmentation. They express the overlap between segmented and ground truth regions, which is important in brain tumor segmentation, and keeping the values of the two parameters proportional during the training and validation phases is crucial for model stability and this is what our proposed model DCB-Unet, as we can see from Figs. 10 11 12 13 14 that the values of the dice and IoU are well matched during the training and validation period, which proves the readiness of the model and its high efficiency in segmenting medical images, especially brain tumors.

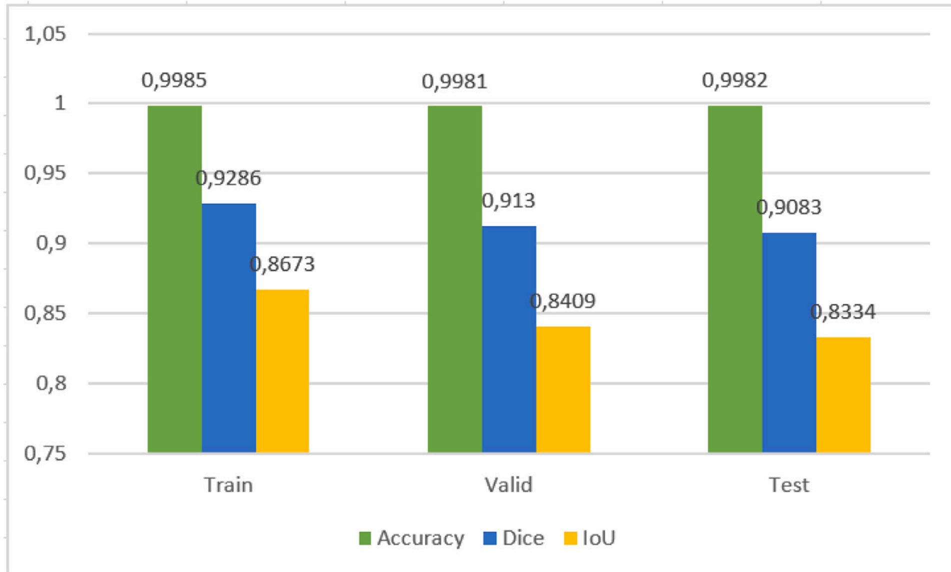


Fig. 9. Bar graph showing the training, validation, and testing parameters.

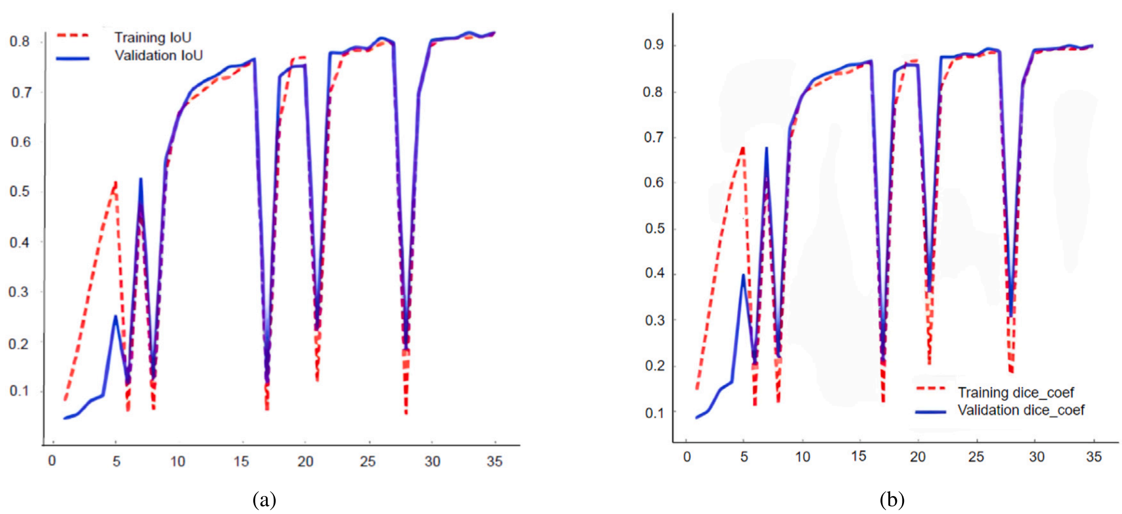


Fig. 10. (a) IoU coefficient plot for Kumar et al. (b) Dice coefficient plot for Kumar et al.

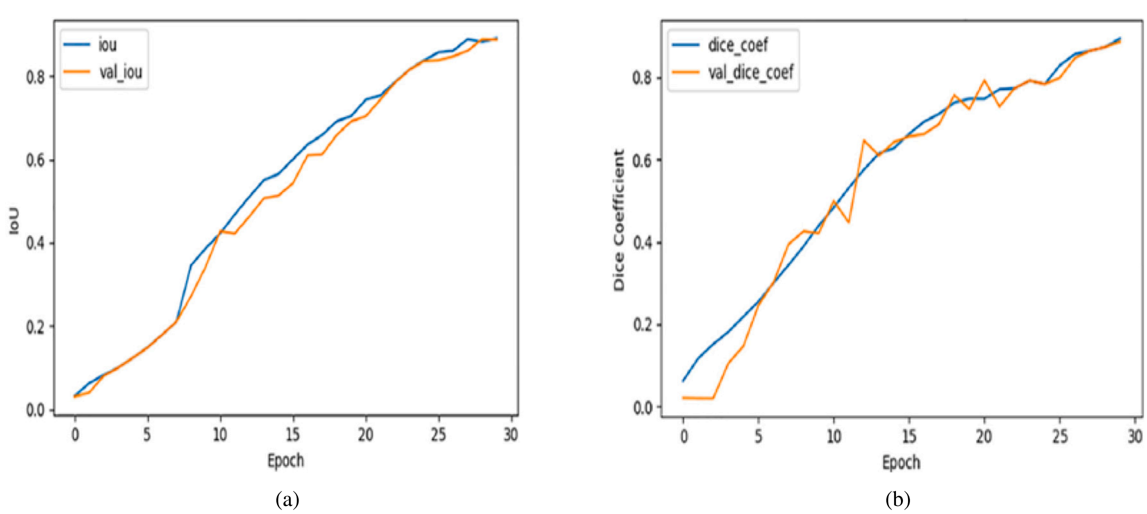
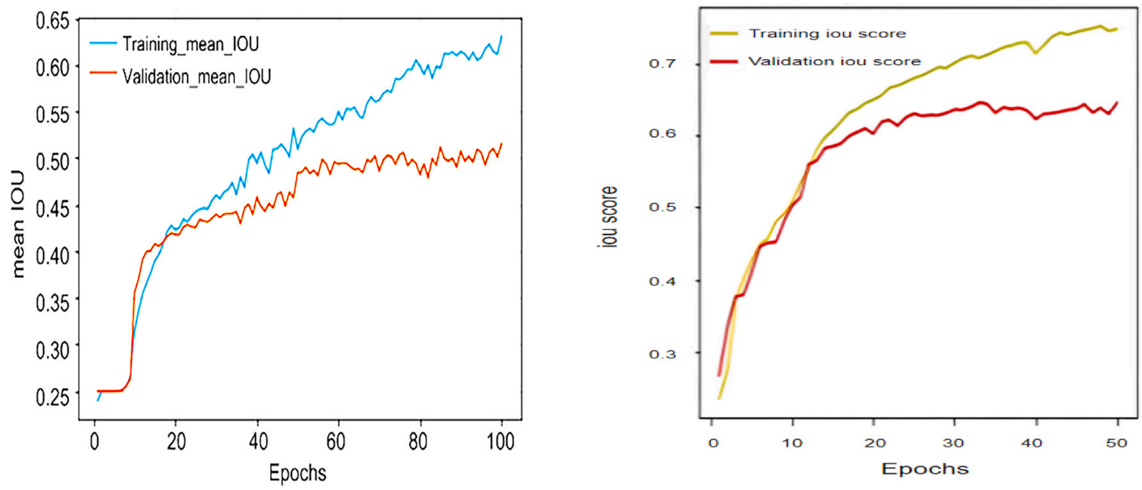
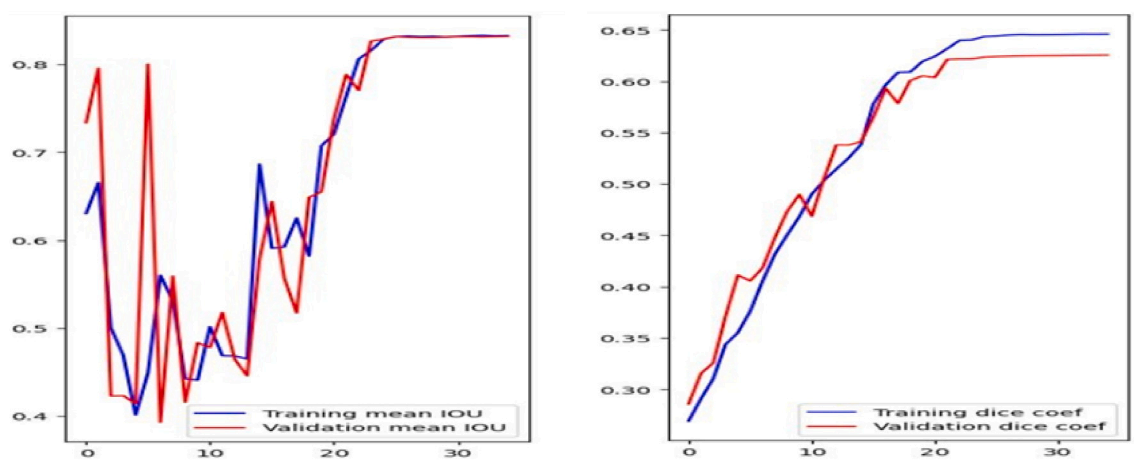


Fig. 11. (a) IoU coefficient plot for Sathish et al. (b) Dice coefficient plot for Sathish et al.



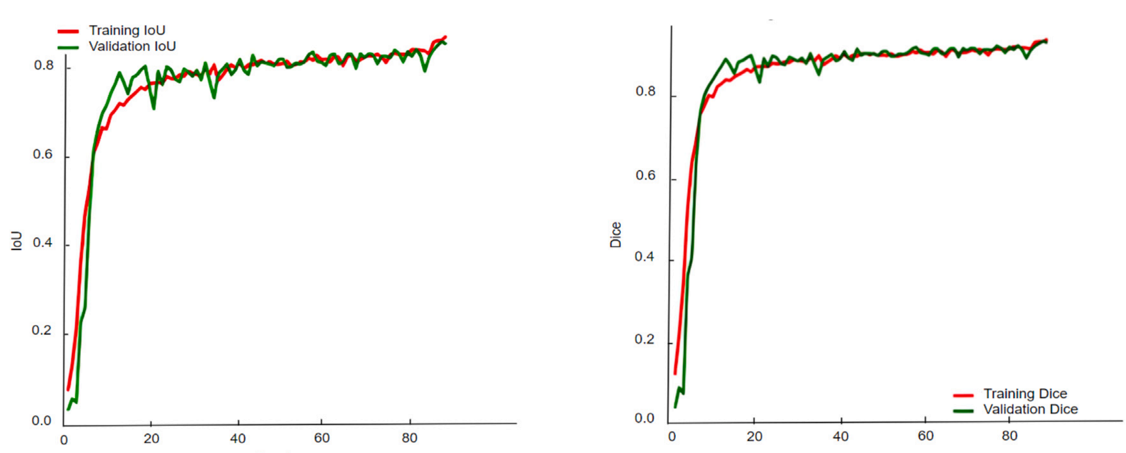
(a) (b)

Fig. 12. (a) IoU coefficient plot for Shomirov et al. (b) Dice coefficient plot for Renugadevi et al.



(a) (b)

Fig. 13. (a) IoU coefficient plot for Joshi et al. (b) Dice coefficient plot for Joshi et al.



(a) (b)

Fig. 14. (a) IoU coefficient plot for proposed approach. (b) Dice coefficient plot for the proposed approach.

5. Conclusion

Current studies in the medical field are highlighting the potential of deep learning models to improve the segmentation of brain tumors due to the importance of their location and risk to human life. Brain tumors pose a challenge to researchers and practitioners due to their heterogeneous sizes, shapes, and ambiguous boundaries between the tumor area and healthy brain tissue. In this article, we presented the DCB-Unet model in which we developed a new technique by integrating depthwise convolution bottleneck blocks into a skip network to help the system retain information about spatial transitions between inputs and outputs while improving quality, deep learning techniques showed promising results in brain tumor segmentation but the DCB-Unet model performed better compared to state-of-the-art works, the proposed system is not perfect but offers very excellent performance. However, future research should continue to improve deep learning models using different techniques to increase the quality of brain tumor segmentation, we seek to improve our future study by evaluating the model on different datasets to ensure its efficiency and generalizability of the results.

CRediT authorship contribution statement

Lahmar Hanine: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Naimi Hilal:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Formal analysis, Data curation.

Declaration of competing interest

I have no pecuniary or other personal interest, direct or indirect, in any matter that raises or may raise a conflict with my duties as a manager of journal of Engineering Applications of Artificial Intelligence.

I also acknowledge that I shall make another declaration to state any change in any matter contained in this declaration within one month after the change occurs and shall provide further information on the particulars contained in this declaration if so required by the journal of Engineering Applications of Artificial Intelligence.

Data availability

I have shared the link to my Data.

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