Segmentation and classification of brain tumor using 3D-UNet deep neural networks

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ABSTRACT

Early detection and diagnosis of a brain tumor enhance the medical options and the patient's chance of recovery. Magnetic resonance imaging (MRI) is used to detect and diagnose brain tumors. However, the manual identification of brain tumors from a large number of MRI images in clinical practice solely depends on the time and experience of medical professionals. Presently, computer aided expert systems are booming to facilitate medical diagnosis and treatment recommendations. Numerous machine learning and deep learning based frameworks are employed for brain tumor detection. This paper aims to design an efficient framework for brain tumor segmentation and classification using deep learning techniques. The study employs the 3D-UNet model for the volumetric segmentation of the MRI images, followed by the classification of the tumor using CNNs. The loss and precision diagrams are presented to establish the validity of the models. The performance of proposed models is measured, and the results are compared with those of other approaches reported in the literature. It is found that the proposed work is more efficacious than the state-of-the-art techniques.

1. Introduction

Abnormal growth of cells or tissues in the brain can lead to a brain tumor. Neither the exact symptoms of a brain tumor nor the reasons that cause brain tumors are known today. Thus, people may be suffering from brain tumors without realising the gravity of the situation. It is of paramount importance to detect and extract the tumors at their early stages to save the patient's life.

The MRI is an important tool for the detection, diagnosis, and monitoring of brain tumors. However, examining MRI scans is a dexterous, time-consuming, and difficult process. Further, it is very difficult to detect tumors manually, and the results may vary from one clinical expert to another based on their experience. Effective classification and segmentation of MRI images is quite challenging. The rationale is to build an expert system that would assist in the effective diagnosis of cancerous cells in MRI scans of the brain.

Over the years, several researchers from various backgrounds have relied on image recognition techniques for the identification of brain tumor cells (Amin, Sharif, Haldorai, Yasmin, & Sundar Nayak, 2021). To get the optimum performance, they have used a variety of machine learning techniques to detect cancerous cells. Advanced neural networks and deep learning techniques are also utilized. For instance, advanced neural networks, graph-based CNN, and CNN are employed to improve the detection of malignant lesions in breast mammograms (Zhang, Sa-

tapathy, Guttery, Górriz, & Wang, 2021b). A convolutional neural network with exponential linear units and rank-based weighted pooling is implemented for the early diagnosis of optimal therapeutic intervention (Zhang et al., 2021a).

One of the most difficult aspects of dealing with MRI scans is that they are not 2D images like X-ray images. An MRI image is made up of several 3D volumes that show various parts of the brain. Until image segmentation, these 3D volumes are fused. When merging various channels of an MRI image, certain misalignments can occur, resulting in errors that can be corrected by image registration. Image registration is a technique for aligning images. Various machine learning and deep learning models for brain tumor prediction have been proposed recently. Many models for detecting, segmenting, and classifying brain tumors have been presented in the literature. For the segmentation of volumetric MRI scans, convolutional neural network architecture has been considered in this study.

This research work focuses on the development of an effective model that can help in the accurate identification of tumors automatically. The proposed model is built on 3D-UNet convolutional neural networks that have been trained for tumor segmentation. The research is based on 3D segmentation of MRI scans. The volumetric MRI scans' 3D volume is divided into 3D sub-volumes, which are fed into the segmentation model and then recombined into a single 3D volume. The suggested method is useful since it effectively protects all aspects of the image
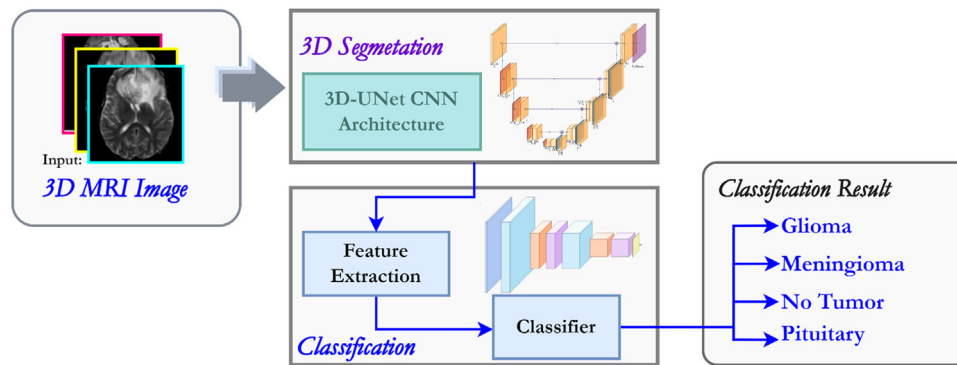
Fig. 1. Abstract view of proposed Brain tumor Detection System.

while maintaining the image's volume. UNet architecture's effectiveness has also been extensively documented in the biomedical literature.

The proposed work takes into account an image registration model, a 3D U-Net model, and finally a soft dice loss feature, all of which have been combined to form a comprehensive tumor detection model. The first move was to merge 3D image slices from an MRI scan into a single 3D model. Image registration corrects misalignment issues during mixing. The 3D model is divided into subsections after it has been developed. The subsections are then passed into the U-Net model, and the segmented model is obtained at the output after both down and up convolution cycles. The subsections are then merged once more to create a segmented 3D model, followed by the estimation of the loss function.

After the volumetric segmentation of the tumor the next step is the classification of the brain tumors into meningioma, glioma, and pituitary tumors. Prior to feature extraction and sorting, most traditional brain tumor classification approaches included region-based tumor segmentation. CNN is made up of a convolutional neural network that performs automated segmentation and feature extraction, supplemented by a classical neural network that performs classification. A Rectified Linear Unit (ReLu), a convolution, and a pooling layer make up CNN's well-known simple architecture.

The abstract view of the proposed framework is presented in Fig. 1. The MRI images will be used as the input. The main phases of the proposed system are divided into four parts:

  i Data Collection
 ii Pre-processing
iii Segmentation
iv Classification

Firstly, the collected images are subjected to the pre-processing module. The corrupted and blurred images are filtered in this module. For efficient and enhanced segmentation and classification, better segmentation and classification models are proposed in the research work.

The major contributions of the paper are as follows:

- The proposed framework incorporated the implementation of an advanced 3D U-Net model for volumetric segmentation and updated CNN for the classification of the MRI images, with the objective of creating an expert system for predicting brain tumors at an early stage.
- The proposed segmentation and classification models are empirically evaluated using various evaluation metrics such as precision, recall, F score, dice similarity co-efficient, and support.
- The loss and precision diagrams have also been used to establish the validity of the models.
- The results are compared with the other approaches reported in the literature, and established as being more efficacious than the state-of-the-art techniques.

2. Related work

Over the years, many specialists from diverse backgrounds have worked and are still working within the domain of image processing, dealing with the detection and classification of various cancerous diseases like brain tumor, kidney tumor etc., and have proposed many novel procedures to generate the best results.

Wadhwa, Bhardwaj and Verma (2019) examined various methods for tumor identification and proposed that combining Conditional Random Field (CRF) with FCNN and CRF with Deep Medic or Ensemble offers better performance than the other approaches for tumor segmentation. In Özyurt, Sert, Avci and Dogantekin (2019), for segmentation, Fatih Zyurt et al., proposed the use of the neutrosophic set expert maximum fuzzy-sure entropy (NS-EMFSE) process, and SVM and KNN classifiers were used to remove segmented functionality from the CNN architecture. Recently, CNN has been employed by many researchers for image classification in the domain of medical sciences (Ayadi, Elhamzi, Charfi, & Atri, 2021; Jin, Meng, Sun, Cui & Su, 2020; Kalaiselvi, Padmapriya, Sriramakrishnan & Somasundaram, 2020; Mohsen, El-Dahshan, El-Horbaty & Salem, 2018; Murthy, Koteswararao & Babu, 2022; Rehman et al., 2021; Suganthe, Revathi, Monisha & Pavithran, 2020). Good performance results are reported using advanced neural network models for MRI scan classification (Liu et al., 2018; Abiwinanda, Hanif, Hesaputra, Handayani & Mengko, 2019; Afshar, Mohammadi & Plataniotis, 2018; Badža & Barjaktarović, 2020; Bedekar, Niharika Prasad, & Revati Hagir, 2018). Automated classification is very useful in computer-aided diagnosis systems. Ensemble models combining SVMs and neural networks are also implemented for the design of medical diagnosis systems (Deepak & Ameer, 2021). Soft computing techniques like fuzzy logic are also incorporated for better results (Jayachandran & Dhanasekaran, 2013). Advanced fuzzy methods like adaptive fuzzy C-means clustering are used for segmentation. Results are further improved by the deer hunting optimization algorithm (Murthy et al., 2022).

Li, Kuang, Xu and Sha (2019) proposed a multi-CNN approach to tackle the poor performance offered by the conventional methods. The conventional models have slow training rates and often suffer from overfitting. The proposed method uses 3D-MRI images to train the neural network for volumetric segmentation as compared to 2D-MRI images. The method employs the use of three-dimensional CNNs for this purpose for the volumetric detection of the tumor in the 3D-MRI images. The work also concludes that instance normalization consumes less time to train the 3D-CNN as compared to batch normalization and group normalization methods, and the proposed 3D-CNN model for the brain tumor detection offers better accuracy and performance. An algorithm for 2D MRI scans is also proposed for segmentation and classification of MRI scans. Deep neural network algorithms with different activation functions like SoftMax and sigmoid are also implemented (Chattopadhyay

& Maitra, 2022). Some researchers have also deployed a user-friendly computer-aided interface for MRI scan classification (Ucuzal, Yaşar & Çolak, 2019).

Sobhaninia et al. (2018) suggested that medical image recognition relies heavily on image segmentation, because medical photographs are too diverse, and used MRI and CT scan images to segment the brain tumor. The most common use of MRI is for brain tumor segmentation and classification. They proposed the use of fuzzy C-Means clustering for tumor segmentation, which can reliably model tumor cells. After segmentation, classical classifiers and CNNs were used to classify the data. They implemented and compared the effects of various conventional classifiers such as K-Nearest neighbour, logistic regression, multilayer perceptron, nave bayes, random forest, and support vector machine in the traditional classifier section. SVM had the best precision of 92.42 percent among these conventional ones. They also introduced CNN, which yielded 97.87 percent accuracy with a split ratio of 80:20 of 217 photographs, and suggested to experiment with 3D brain images in the future to accomplish more effective brain tumor segmentation. Working with a wider dataset would be more difficult in this regard, and they aspired to create a dataset that emphasizes the abstract in relation to their region, which will help them expand the reach of their research.

In Zhou et al. (2020), a web-based application that can identify brain tumor (glioma, meningioma, and pituitary) based on high-precision T1 contrast MRI with CNNs. It is hoped that the free web-based software would enable medical professionals and other health professionals to identify brain tumors more quickly and accurately. In this regard, the app can be used as a clinical-decision support method for brain tumor classification (i.e., glioma, meningioma, and pituitary). According to the experimental findings, all of the measured success metrics for classifying the forms of brain tumors on the training dataset were greater than 98%. On the research sample, all performance metrics are greater than 91%, with the exception of the sensitivity and Matthews correlation coefficient (MCC) performance metrics for meningiomas. When the measured efficiency metrics from the CNN model's training and testing stages are considered, the proposed model is capable of effectively classifying various brain tumor forms. A new research study created the CNN to identify brain tumor on public data sets, with 233 and 73 patients, and 3064 and 516 images on T1-weighted magnetic resonance images. For the two datasets, the method built in this trial performs significantly better and is able to effectively identify brain tumor multi-classification jobs at the highest overall accuracy levels of 96.13% and 98.7% respectively. A new algorithm for the classification of brain tumor in Grade I, Grade II, Grade III and Grade IV of the CNN profound learning algorithm was also developed. The proposed algorithm for deep learning consists of three steps: a) tumor segmentation, b) data increase, and c) profound extraction and classification functions. Experimental findings from the other research work were investigated and showed that, when extended to augmented and initial data sets, the proposed algorithm has greater efficiency than the present methods. The classification and simulation of T1-weighted MRI of brain tumor were well performed during previous experiments in machine learning and deep learning algorithms. But the selection and development of these algorithms may take a lot of time and experience if we consider the machine learning and data mining applications of the studies published over the past few years. Therefore, in recent years, automated machine learning and various modelling systems have been widely developed. To put it briefly, the current research introduces a novel public web-based program to identify brain tumor types based on CNN's profound learning algorithms for T1-weighted MR images.

Yadav and Sahu (2013) presented a novel approach for the automatic segmentation of the most popular brain tumor, including gliomas, meningiomas, and pituitary. No preprocessing steps are essential for this technique. The findings show that angle-based dividing of photographs increases dividing precision. The highest score for the dice was 0.79. The tumor segmentation in sagittal view images provided this comparatively high ranking. Other organs are not visible in sagittal images, and the tu-

mor is more pronounced than in other images. The photographs from the axial view of the head received the lowest dice score in their tests, which has been reported as 0.71. The axial view provides less specificity than the other pictures. It is anticipated that preprocessing this group of images would result in improved tumor pixel classification and an improvement in the dice ranking. The presented approach may be used to segment brain tumor in MRI images as an easy and practical technique for doctors.

In Murthy and Sadashivappa (2014), MRI studies indicate that the cancer-affected region has very high intensity pixels, whereas normal tissue has low intensity pixels. Thresholding is a method of segmentation that uses only the sensitivity parameter. This is one of the most basic types of segmentation, in which the tumor is classified according to its grey level.

Area-based image segmentation (Alqudah, Alquraan, Qasmieh, Alqudah & Al-Sharu, 2020) involves developing regions. Method uses 4-connected neighborhood or 8-connected neighborhood methodology. The amplitude of the same picture is clustered in one area. If the intensity belongs to the same seed, the phase is iterated, and the intensity belongs to one field. Geometric active contour models focused on regions are more resistant to noise in the MRI, which leads to poor segmentation. T.S. Deepthi Murthy et al. (Kaur & Gandhi, 2019) proposed thresholding and morphological operations that are used to perform effective brain tumor segmentation. However, since the threshold value used is a global threshold, it is not completely automatic and requires human interference. In Kavita, Alli and Rao (2022), a study has been presented on the multimodal medical image fusion technologies using pulse coupled neural networks with QCSA and SSO optimization techniques. In Kalaivani and Seetharaman (2022), a three-stage boosted ensemble convolutional neural network has been proposed for the classification of COVID-19 chest x-ray images. The proposes the development of an extended U-Net architecture using ResNet architecture as a backbone. In Muruganantham and Balakrishnan (2021), a survey has been carried out for the various deep learning methodologies used to detect various gastrointestinal tract diseases.

3. Methods and materials

The proposed segmentation and classification models are explained in this section.

3.1. Segmentation model

i Dataset

In multimodal magnetic resonance imaging (MRI) scans, BraTS has always concentrated on evaluating cutting-edge techniques for brain tumor segmentation. BraTS 2020 segments intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, such as gliomas, using multi-institutional pre-operative MRI scans. BraTS'20 also uses integrative analyzes of radiomic features and machine learning algorithms to pinpoint the clinical validity of this segmentation task, as well as estimate patient overall survival and the discrepancy between faux progression and actual tumor recurrence. Finally, BraTS'20 attempts to evaluate the algorithmic sophistication of tumor segmentation.

i 3D-Unet

U-Net is one of the most popular architectures used for segmentation. It was designed for image segmentation in the biomedical field. It produced great results for cell tracking. It can work with hundreds of examples and produce good results. As it is U-shape so it is called the U-net model. It consists of two paths: the contracting path and the expanding path. Both paths perform opposite results. The contracting path involves down sampling and down convolution. Expanding paths involves up-sampling and up-convolution. In contracting path feature maps get spatially smaller, whereas in an expanding path, the feature
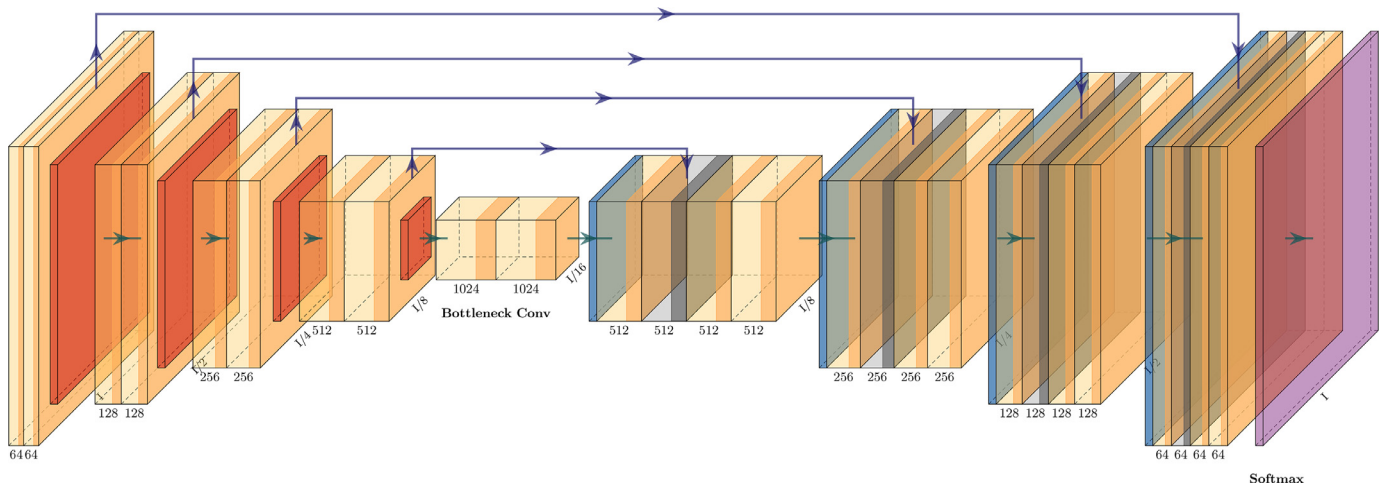
Fig. 2. 3D-UNet structure.

maps are expanded back to their original size. This model was basically built for 2D images, but by replacing 2D convolutional networks with 3D networks the model can be used for 3D convolution as well. Fig. 2 shows the architecture of the 3D-Unet deep neural network architecture.

i Proposed Segmentation Model

The 3D U-Net model is the model introduced in this paper. The models that make up the full tumor detection platform are an image registry model, a 3D U-Net model, and soft dice failure. The first step was to combine 3D image slices from an MRI scan into a single 3D model. Image registration is used to solve misalignment issues during combination. Following the formation of the 3D model, the 3D model is divided into subsections, each of which is coded in the appendix. The subsections are then fed into the U-Net model, which produces the segmented model after all of the down and up convolution cycles. The subsections are then merged once more to create a segmented 3D model. The next move is to calculate the damage.

3.2. Classification model

3.2.1. Dataset

The classification model is based on the *Brain* tumor *Classification* (MRI) Kaggle dataset. This dataset is split into training and research sets, accumulating 3264 files categorized as glioma, meningioma, pituitary, and no tumor photographs. Since this is a classification model, this dataset aids in the accurate and precise training and testing of the model.

3.2.2. Convolutional neural network

Neural network architecture is inspired by the biological human brain. Neural networks are primarily used to quantify vectors, approximate data, cluster data, align patterns, optimize, and classify functions. Based on their links, the neural network is categorized into three groups, viz., (a) feedback, (b) feedforward, and (c) recurrent networks. Further, a neural network can be classified as a single-layer network or a multilayer neural network.

The picture cannot be scaled in the standard neural network. However, in the convolution of the neural network, pictures can be scaled (i.e. in length, width, and height). The Convolution Neural Network (CNN) consists of an input layer, a convolution layer, and a rectified linear unit (ReLu). The provided input picture is divided into several small regions of the convolution sheet. In the ReLu layer, element-wise feature activation is performed, and an optional pooling layer could be used. The pooling layer is used primarily for sampling purposes. A class score or mark score value dependent on chance between 0 and 1, is used in the last layer (i.e., to produce the completely connected layer).

Fig. 3 shows the block diagram of the grouping of brain tumor based on the neuronal network. The classification of brain tumor based on CNN is split into two stages: (a) preparation and (b) research. The number of photographs is categorized by naming the marks (tumor, non-tumor images, etc.) into various categories. In the training step, pre-processing, functional extraction and loss function classification are carried out to produce a prediction model. First, the picture collection is marked for the instruction, and then the image is resized to adjust the image size in the pre-processing process. Finally, for the automated detection of brain tumor the neural convolution network is used.

The brain image dataset used for this model is taken from Kaggle. To use the untrained dataset, the model is trained from layer one until the end layer. This can be very time-consuming and will also affect the outcome. So, for classification measures, a pre-trained model-based brain dataset is used to prevent this issue. In the proposed model, only the last layer is trained during implementation. As a result, the proposed model has a short computing period with higher efficiency.

The loss function is determined by the gradient descent algorithm. The raw pixel image is mapped using a score feature to achieve class results. Quality is calculated by the loss function of a particular set of parameters. It is dependent on the way induced results are accepted in the training data with the ground truth marks. In order to increase the precision, calculating the loss function is extremely necessary. When there is a high loss function, the precision will be very poor. Similarly, when the loss function is minimal, the precision will be high. The value for the loss function is determined to estimate the downward gradient algorithm, and it accesses the gradient value to calculate the loss function gradient repeatedly.

3.2.3. Proposed segmentation model

The proposed model in this paper is a newly developed CNN architecture. The proposed architecture is novel because it is updated. The design has 16 layers to enable the classifier to efficiently classify the brain tumor images. The configuration of the implemented CNN architecture is presented in Fig. 4.

4. Results and discussion

The results of segmentation and classification models are explained in this section.

4.1. Segmentation results

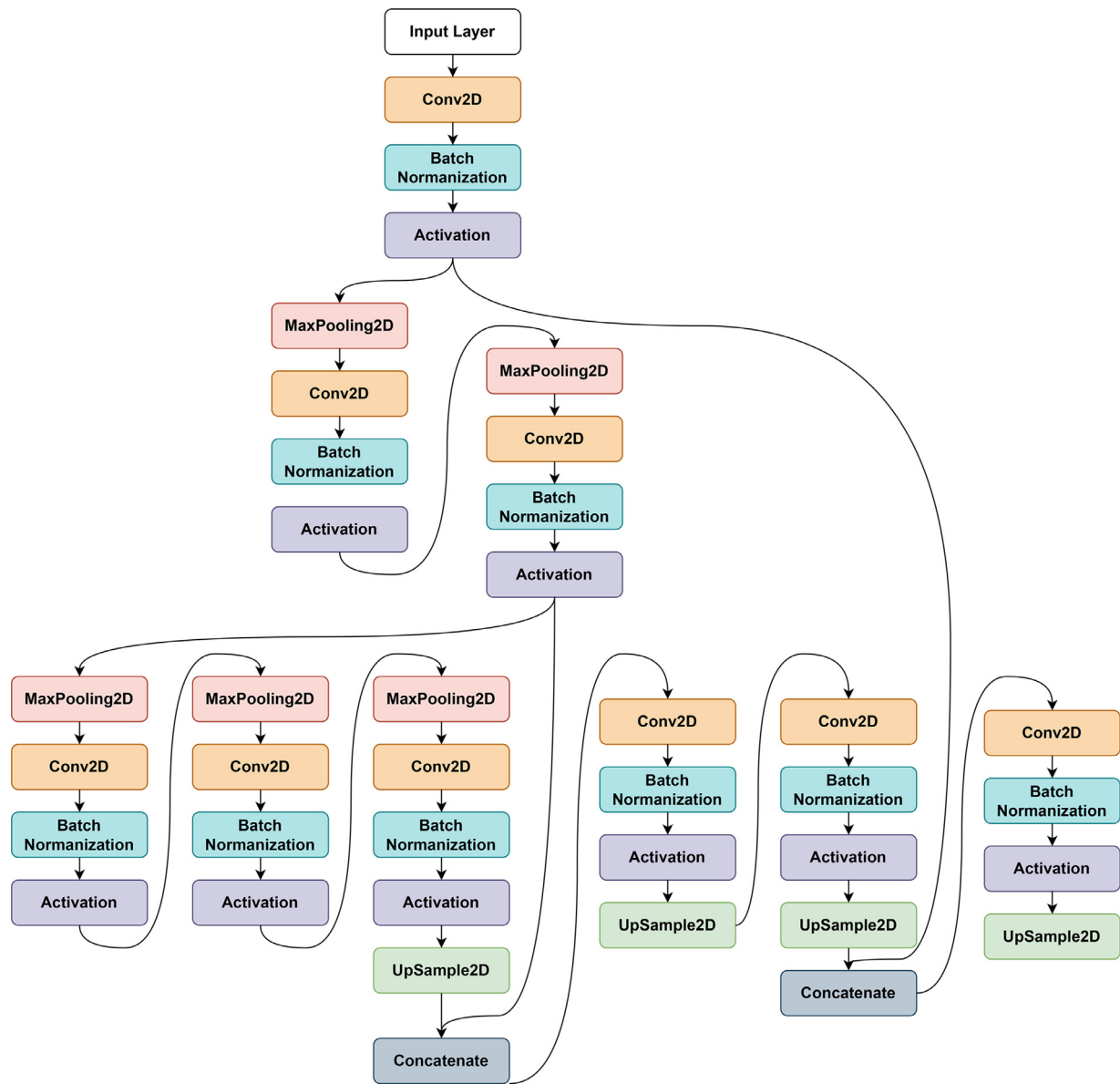The results of the segmentation model are presented in this section.
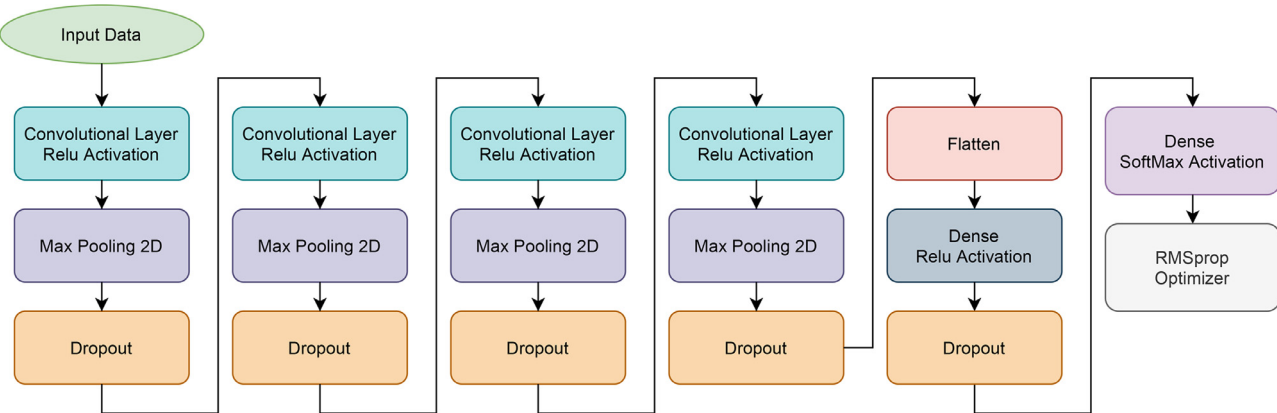
Fig. 3. Segmentation and Detection model.

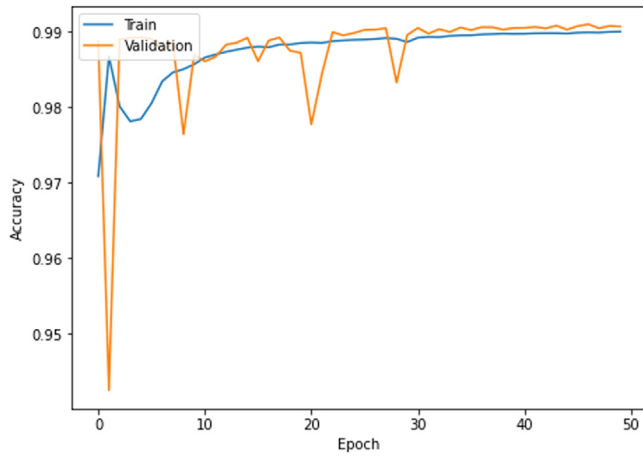**Fig. 4.** Proposed Classification Model.
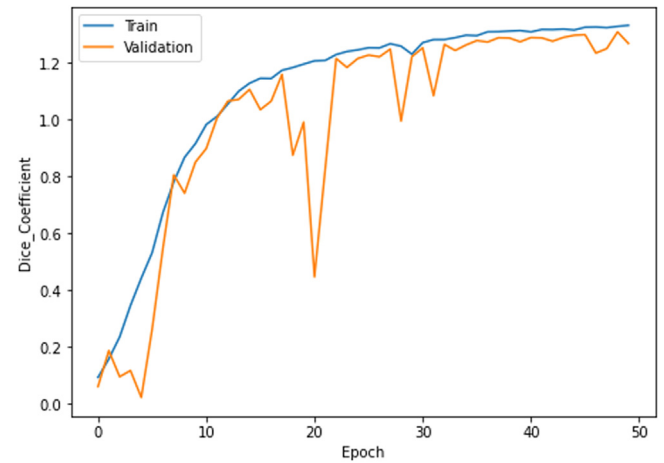
Fig. 5. Accuracy graph.

Fig. 6. Dice coefficient graph.

4.1.1. Evaluation matrices used for segmentation

Besides architecture, loss function is also an important segment of deep learning. Soft dice loss is a popular loss function for loss detection in segmentation models. It works well with imbalanced data. So, it is specially used for brain tumor segmentation.

$$\mathcal{L}_{Dice}(p, q) = 1 - \frac{2 \sum_{i,j} p_{ij} q_{ij} + \epsilon}{\left(\sum_{i,j} p_{ij}^2\right) + \left(\sum_{i,j} q_{ij}^2\right) + \epsilon}$$

Where, p is for predictions and q is for ground truth. ϵ is a small number to avoid division by 0.

The equation is subtracted from 1, so that higher overlap gives a low loss and low overlap gives a high loss. The *DSC (dice similarity co-efficient)* is a metric that calculates the overlap between manually delineated brain tumor regions and the segmentation results of the proposed fully automated process. The number of false positives divided by the number of positives plus the number of false positives is the "dice score" (DSC) in mathematics.

$$DSC = \frac{2TP}{FP + TP + FN}$$

$$Dice\ Loss = \frac{2\left|x_1 \cap y_1\right|}{|x_1| + |y_1|}$$

4.1.2. Performance analysis of segmentation

Figures below show the performance evaluation of the proposed model. Fig. 5 shows the accuracy plot. From the plot, it can be observed that the proposed model converges after around 40 epochs, and an accuracy of about ~99% has been achieved for both the training and the validation data.

Fig. 6 shows the plot for the dice coefficients. Fig. 7 shows the plot for the loss function for both the training and the validation sets. The various performance parameters are given below. It can be observed that an accuracy of about 99.06% has been achieved. Fig. 8 shows the segmentation results for eight different samples.

The complete results are presented in Table 1. The implemented model shows good performance with loss, accuracy, dice co-efficient, precision, sensitivity, and specificity of 0.17, 99.06%, 1.28, 088, 0.97, and 0.99 respectively.

4.2. Classification results

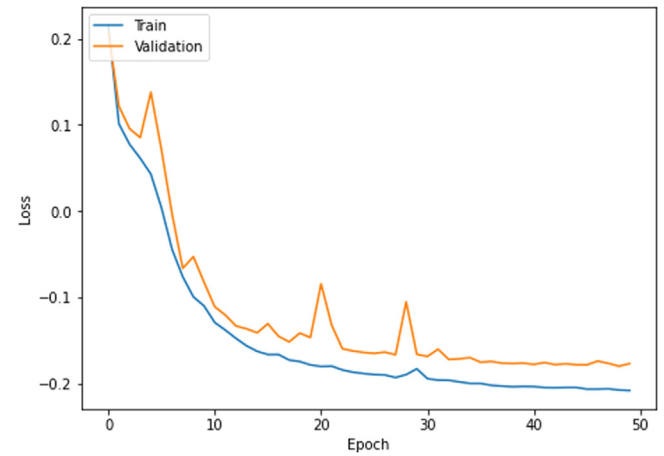The results of the classification model are presented in this section.

Fig. 7. Loss graph.

Table 1
Summary of Results.

Performance Metric	Results
Loss	0.17
Accuracy	99.06%
Dice Co-efficient	1.28
Precision	0.88
Sensitivity	0.97
Specificity	0.99

4.2.1. Evaluation metrics
- Accuracy:

Accuracy is one metric for classification models to be assessed. By using the following theorem, we can conveniently determine precision via the uncertainty matrix.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP: True Positive; FP: False Positive; TN: True Negative FN: False Negative

- Loss:

For upgrading the weight vector, loss functions are used by using the labelled and measured model outputs. This paper uses two widely used failure methods, "Gradient Downward" and "Middle-Square-Error" Mathematical decision and optimization theory show that a loss function or a cost function may map an event with one or more variables to a
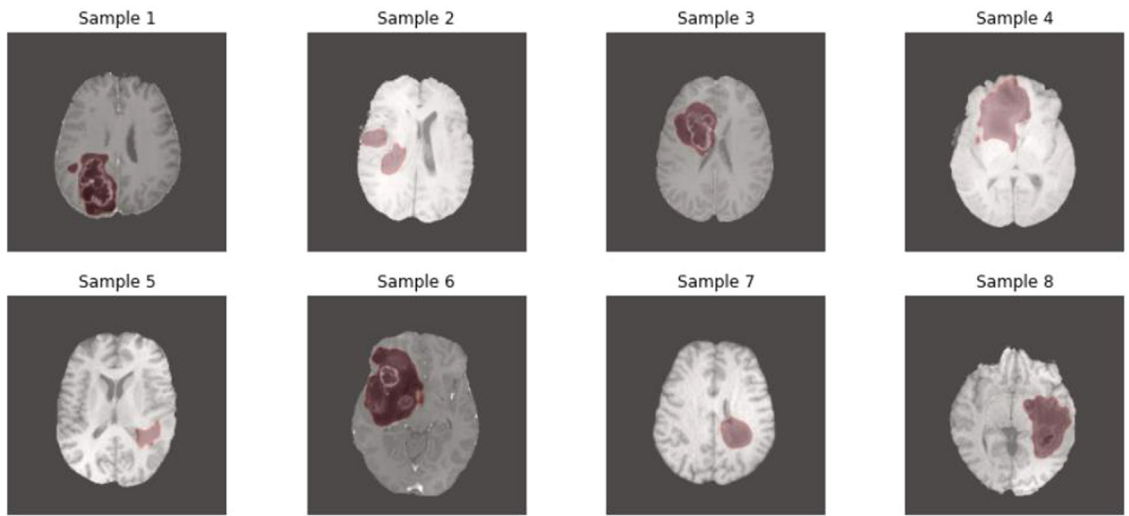
Fig. 8. Example of brain tumor detection.
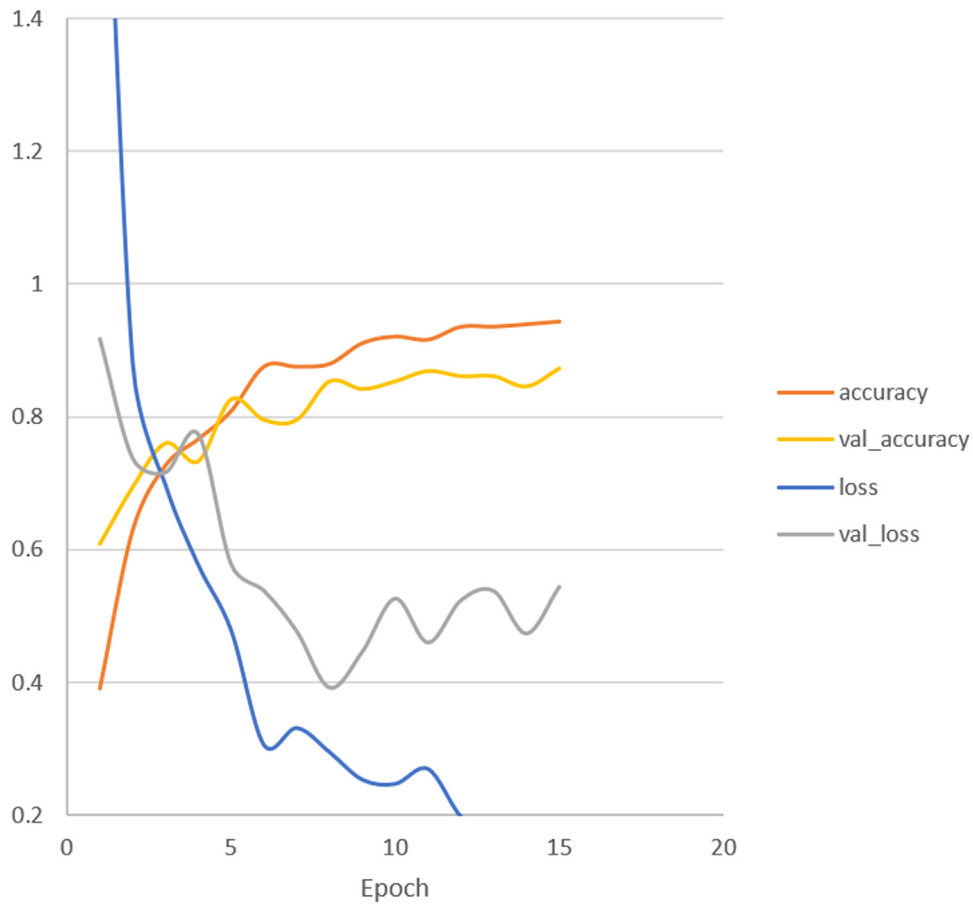
Fig. 9. Loss and accuracy graph.

real number that intuitively represents some cost in conjunction with the event.

- Precision:

The number of true positives divided by the number of true positives plus the number of false negatives is the definition of precision.

$$Precision = \frac{TP}{TP + FP}$$

- Recall:

Sensitivity is the term for recall. It's a percentage of the overall number of relative instances that were currently found.

$$Recall = \frac{TP}{TP + FN}$$

- F1 Score:

Fig. 10. Training images used for training the classification model.

Fig. 11. Results obtained for the Classification of Brain tumor.
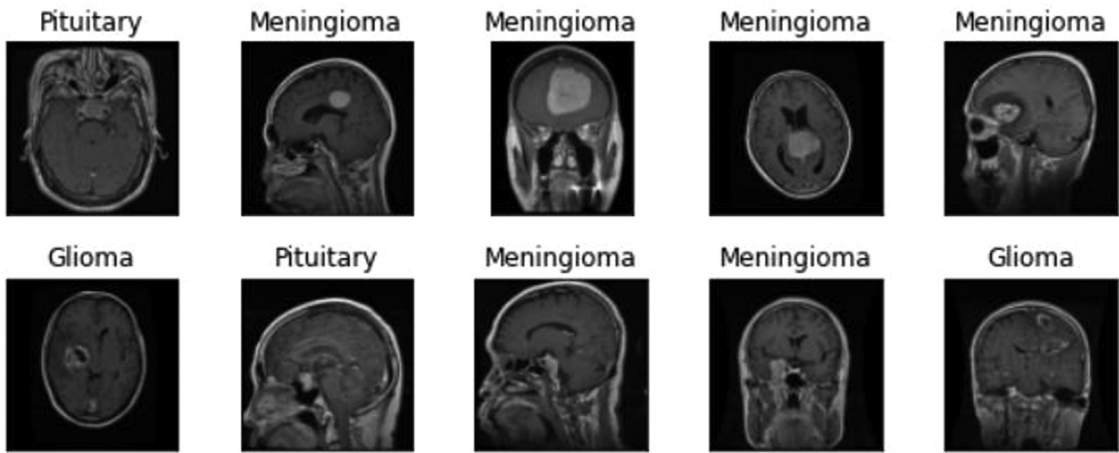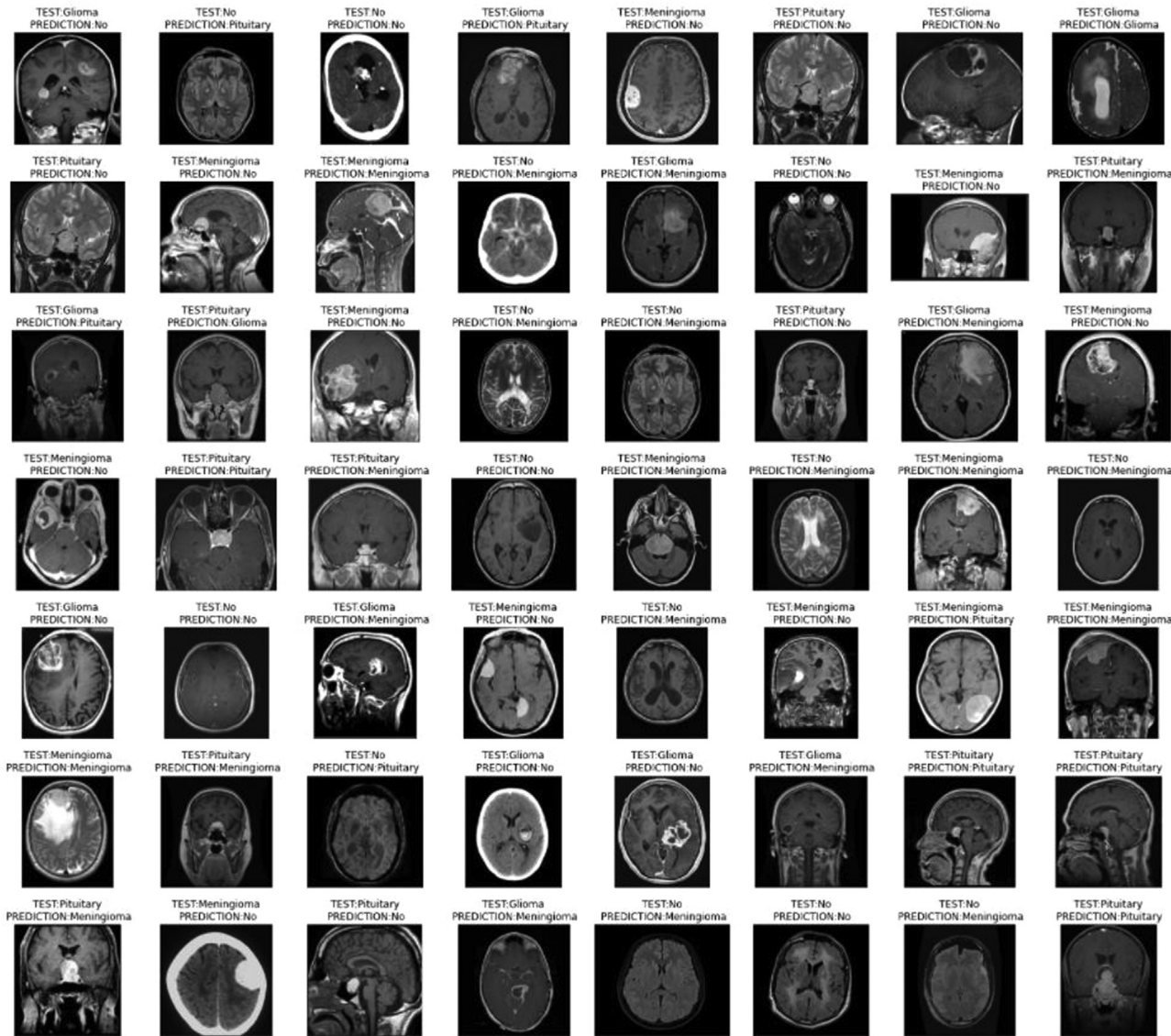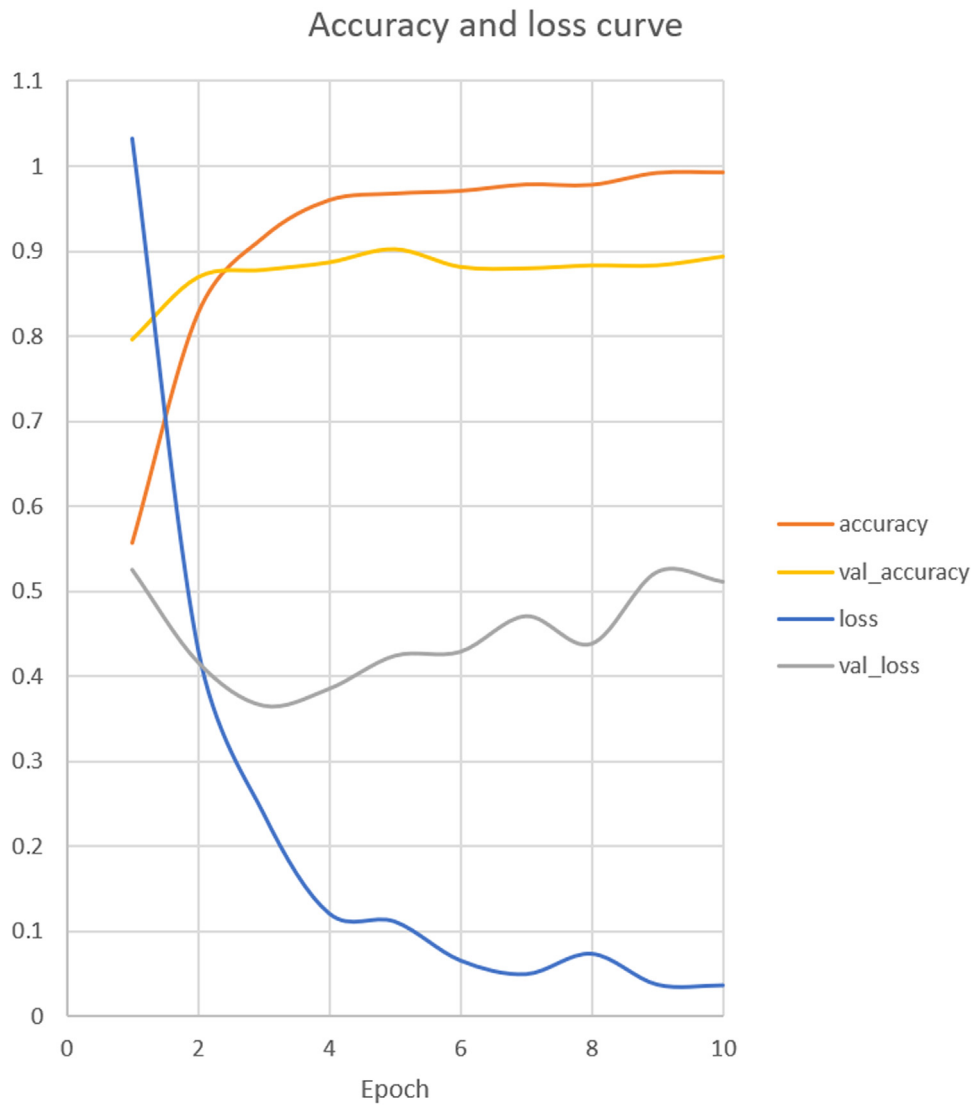
Fig. 12. Loss and accuracy plots for the classification model based on VGG16.

In the following equation, F1 Score is the weighted average or harmonic mean of Precision and Recall, taking all parameters into account:

$$F1\ Score\ =\ 2*\frac{precision\ *\ recall}{precision\ +\ recall}$$

When dealing with an unbalanced dataset, the F1 score is preferred over precision because it accounts for both false positives and false negatives. Using a weighting parameter (beta), F-measures are used to balance the ratio of false negatives.

$$F\ =\ P\ *\ R\ \frac{(1+\beta)^2}{(P+R)\beta^2}$$

Fig. 8 shows the plot for the accuracy and the loss function for the segmentation part. It can be observed from the figure that as the loss minimizes, the accuracy increases, and an accuracy of 94.42% has been achieved while the loss has been reduced to 0.1691. The value of the validation loss has also been reduced to 0.5434, and resulting in a validation accuracy of 87.21%. Fig. 9 shows the plot fot the training and validation accucacy and loss for the classification model.

Table 2 shows the values of various performance metrics obtained for all four classes after the classification. It can be observed in the results the some of the classes like glioma shows low precious and recall value. This may happen due to the lack of samples of a particular class. The

Table 2

Various classification performance metrics for the proposed classification model.

	Precision	Recall	F1-score	Support
Glioma	0.24	0.04	0.07	100
Meningioma	0.24	0.33	0.28	115
No tumor	0.30	0.46	0.36	105
Pituitary	0.25	0.19	0.21	74
Average	0.25	0.25	0.23	394

average of the results is calculated for the comprehensive assessment of the model. It is realized the average performance while considering all four classes is satisfactory with precious, recall, F1 score, and support of 0.25, 0.25, 0.23 and 394 respectively.

Fig. 10 shows the various training images that have been used while training the classification model. Fig. 11 shows the figure for the classification results obtained after inputting an MRI image to the classification model.
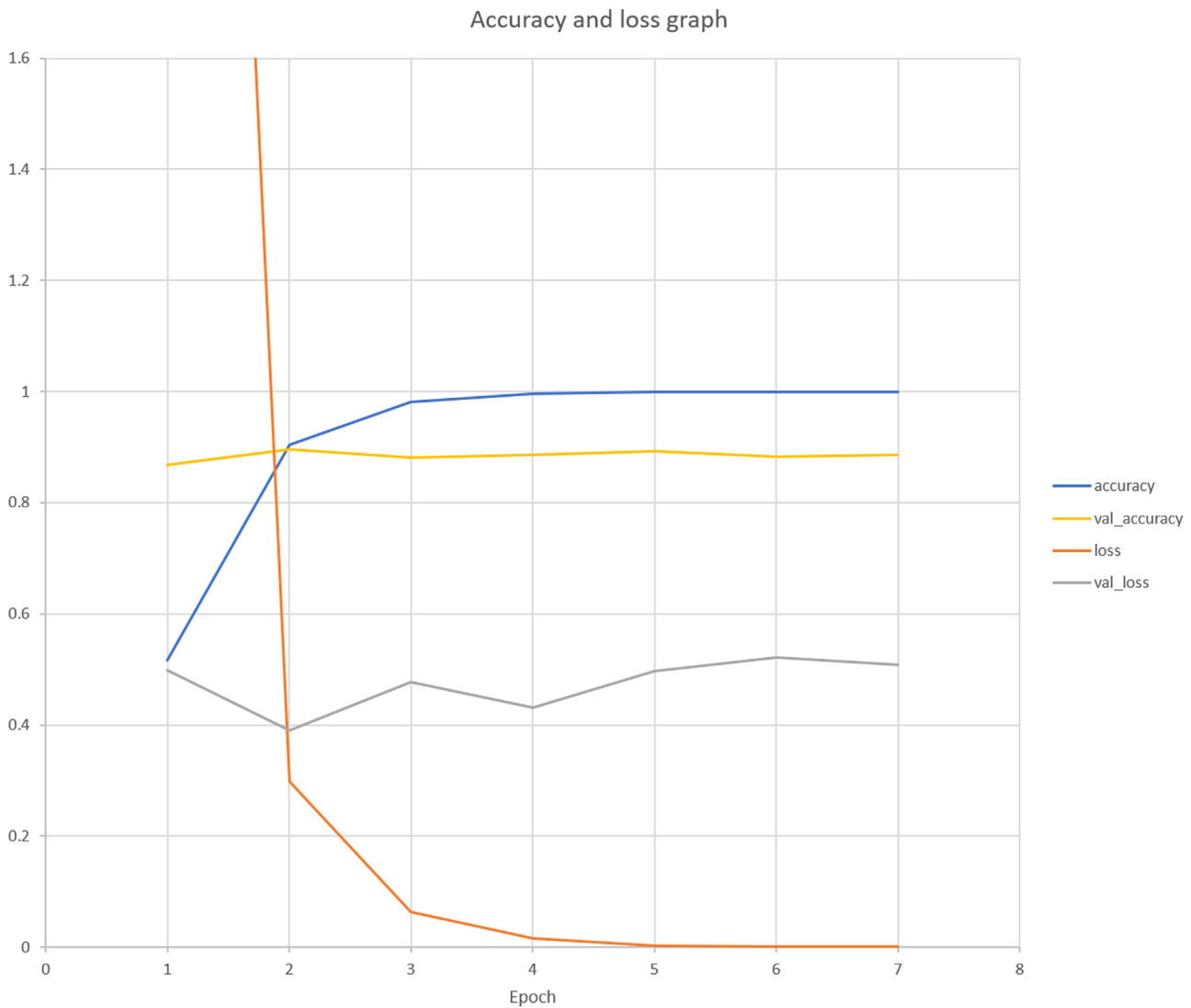
Fig. 13. Loss and accuracy plots for the classification model based on TensorFlow.

Table 3
Various classification performance metrics for the VGG16.

	Precision	Recall	F1-score	Support
Glioma	0.90	0.18	0.30	100
Meningioma	0.76	0.83	0.79	115
No tumor	0.54	0.95	0.69	105
Pituitary	0.81	0.69	0.74	74
Average	0.75	0.66	0.63	394

Table 4
Various classification performance metrics for the TensorFlow.

	Precision	Recall	F1-score	Support
Glioma	0.86	0.19	0.31	100
Meningioma	0.81	0.83	0.82	115
No tumor	0.56	0.96	0.71	105
Pituitary	0.86	0.85	0.86	74
Average	0.77	0.71	0.67	394

4.2.2. Comparison of models for classification of brain tumors

Alqudah (Alqudah et al., 2020) proposed a comparable architecture of 18 layers for OCT image classification. The proposed work has also been compared with two different techniques: the first one considers the transfer learning approach by using the VGG-16 model as proposed in Kaur and Gandhi (2019), and the second methodology is based upon the use of MRI image classification techniques using TensorFlow (Pawlowski et al., 2017). The plots for loss and accuracy are shown in Figs. 12 and 13 for VGG-16 and image classification techniques, respectively. Tables 3 and 4 explain the classification results for both of these models.

Table 5 compiles all the comparisons of the test accuracy and the test loss for all the methods. It can be observed that the proposed classifica-

Table 5
Compared various classification performance metrics.

MODEL	TEST ACCURACY (%)	TEST LOSS
Proposed CNN model	90	0.63
VGG16 (Kaur & Gandhi, 2019)	67	4.3
TensorFlow Example (Pawlowski et al., 2017)	71	4.5

tion model gives the best performance and the minimum values for the loss function and has been established to efficacious than the state-of-the-art techniques. It can be proved that advanced neural networks like CNNs have huge potential for brain tumor detection. The development

of an online platform or service that caters to the need of the patient to upload the scans and the severity of the tumor can also be estimated. This will not only improve the disease prognosis but also make such services accessible to the masses globally. In the future, the potential applications of these applications can be in telemedicine, where, via a digital platform like a website or a mobile application, the records of the scans of the patients can be stored and will be accessible to the doctors so that the tumor progression can be monitored automatically. This will aid in the wider applicability of artificial intelligence to the global population.

Further, the incorporation of the new AI techniques will enhance the results and overall consistency of the classifications. As more and more datasets are now available, the number of output groups can also be expanded, which will significantly improve the total classification precision. Also, increasing the number of cached layers in the deep neural network will be another solution for improving the result. For the developed CNN models, hyper-parameter tuning can also be done to further improve the segmentation and classification precision.

Automated brain tumor segmentation is still a challenge for cancer diagnosis. The availability of public data sets and the well accepted BRATS benchmark recently offered the researchers a popular tool for developing and evaluating their approaches critically using existing techniques. CNN has the benefit of automated learning of representative complex features directly from multi-modal MRI images for both healthy brain tissues and tumor tissues. The development of new methods, such as positron emission tomography (PET), magnetic resonance spectroscopy (MRS), and diffusion tensor imaging (DTI), may improve the current methods through further improvements and modifications to CNN architectures and by providing supplementary information on other imaging modalities. By having more brain MRI images with varying weights and different methods for contrast improvement, this quality can also be enhanced by allowing the design to be theoretically more common and stronger for large image databases.

4.3. Limitations and future scope

(a) **Limitations:** As, to train the DNNs, large training samples are desired. The restricted data availability and high computational cost are the main disadvantages of applying 3D deep learning to medical imaging. Dimensionality is another problem, as it is difficult to process and augment the 3D data, and requires high end GPUs. Another limitation is with the use of 2D ANN kernels as they can't be used for the 3D volumetric data.

(b) **Future Scope:** Regardless of the high computation costs, 3D DNNs have an incredible scope in the several medical applications. Using the interpolation techniques, the overall size of these medical image volumes can be significantly reduced. Concepts of ghost imaging can also be incorporated to enhance the dataset. The generative adversarial networks can also be employed. It can be of great help for clinical experts if exact location and early detection of tumor can be done with ease. This can help in reducing the human errors and variation in result due to manual judgements.

5. Conclusions and future scope

In this study, segmentation and detection of brain tumor have been done using deep neural networks. In the present study, the MRI image dataset is used to train the neural network, and then soft dice loss is used to detect losses in the segmented model. Later, the model is trained, rectifying those losses and giving the segmented image as output. Initially, the 3D MRI model is divided into 3D sub-models to pass through the segmentation model. There are two datasets used for the CNN models. Every dataset is taken from different patients from different parts of the world to conquer the problem of generalization. Secondly, the CNN model is implemented in particular for the three most popular kinds

of brain tumor, i.e., glioma, meningioma, and pituitary, to be classified immediately without involving the use of area-based pre-processing procedures. The results obtained establish the efficacy of the proposed work when compared to the models already proposed in the literature.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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