International Journal of Engineering and Techniques-Volume 11 Issue 4, July - August - 2025

Identification and Segmentation of Brain Tumors from Medical Images using Convolutional Neural Networks

Jinen Modi[1], Dhairya Savaliya[2], Bijoyeta Roy[3] and Hardik Joshi[4]

[1]SMIT, Sikkim Manipal University, India
jinenmodi810@gmail.com
[2]Pandit Deendayal Energy University, India
dhairyasavaliya73@gmail.com
[3]Asst. Professor, Sikkim Manipal University, India
bijoyeta.r@smit.smu.edu.in
[4]Associate Professor, Gujarat University, India
hardikjoshi@gujaratuniversity.ac.in

Abstract. Brain tumors can be detected and classified using invasive medical procedures like biopsy. However, biopsy is not usually conducted before definitive brain surgery. With the drastic improvement in the field of computer science and artificial intelligence, algorithms can be developed in order to identify and perform the tumor diagnostics without any need for invasive measures. Convolutional neural network(CNN) is one such algorithm that has shown substantial scope in this very field. The performance of our algorithm on BraTS dataset which is publicly available MRI image dataset (n=3000) is promising in this domain. Our approach is compared with previous classical machine learning and deep learning efforts. The approach discussed in this paper remarkably obtained an accuracy of 0.9868 and outperformed previous methods.

Keywords: Brain Tumors, Convolutional Neural Network, MRI, BraTS dataset

1 Introduction

Tumor is one of the most common brain diseases, so its diagnosis and treatment have a vital importance for more than 4 million people per year in the world which is based on the World Health Organization (WHO) estimates [1]. On the other hand, in recent years, developments in medical imaging techniques have been employed in several domains of medicine, for example, computer aided pathologies diagnosis, follow-up of these pathologies, surgical planning, surgical guidance, statistical and time series analysis.

The analysis and study of the brain is of great interest due to its potential for studying early growth patterns and morphologic changes in the cancer process. Recent studies have demonstrated the potential of a decision support system for detecting tumors in medical images, providing radiologists with a second pair of highly trained eyes [2]. It gives doctors access to additional information present in images that have characteristics generally accepted to be associated with cancer, clusters of bright spots that are suggestive of lesions, patterns suggestive of tissue masses or distortions, and mark regions that have the characteristics of lesions or tumors. Magnetic Resonance Imaging (MRI) techniques are still developing, and recent efforts have been directed primarily at improving image quality and speed of acquisition. MRI provides noninvasive, high quality images of neuro-anatomy and disease processes [2].

We propose an automatic brain tumor identification and segmentation model that can detect, identify and localize brain tumor in magnetic resonance imaging.

2 Methodology

Detection of brain tumors is a complex task. There are a lot of abnormalities in the sizes and location of the brain tumor(s). This makes it really difficult for complete understanding of the nature of the tumor. Moreover, a professional neurosurgeon is required for MRI analysis. Often times in developing countries the lack of skillful medical professionals and lack of knowledge about tumors makes it really challenging and time-consuming to generate reports from MRI [5][6]. So, an automated system can be optimized, preferably deployed on cloud can be of help in solving these issues.

The dataset used for this is called Axial BraTS or Axial Brain Tumor Segmentation [3]. BraTS has always been focusing on the evaluation of state-of-the-art methods for the segmentation of brain tumors in multimodal magnetic resonance imaging scans. BraTS utilizes multi-institutional pre-operative MRI scans and primarily focuses on the segmentation of intrinsically heterogeneous (in appearance, shape, and histology) brain tumors.

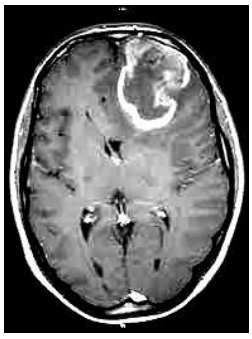

Fig. 1 BraTS Axial Image Data with a tumor

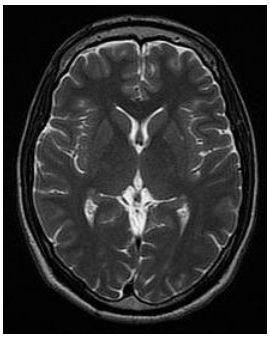

Fig. 2 BraTS Axial Image Data without a tumor

2.1 Image pre-processing and its data augmentation

Magnetic resonance images from the dataset were of varying sizes. These images were normalized and resized to 128 x 128 pixels. Furthermore, the images were rescaled with a rescaling factor of 1/255. Shear intensity of 0.2 is applied. Zoom range of 0.2 is applied. Finally, random horizontal flips were also enabled.

2.2 Proposed CNN implementation and its details

In this paper, the proposed convolutional neural network architecture in a single pathway architecture. The CNN architecture processes an MRI image (slice) pixel by pixel covering the entire image and classifying each pixel using one of the two possible output labels i.e., yes (1) or no (0).

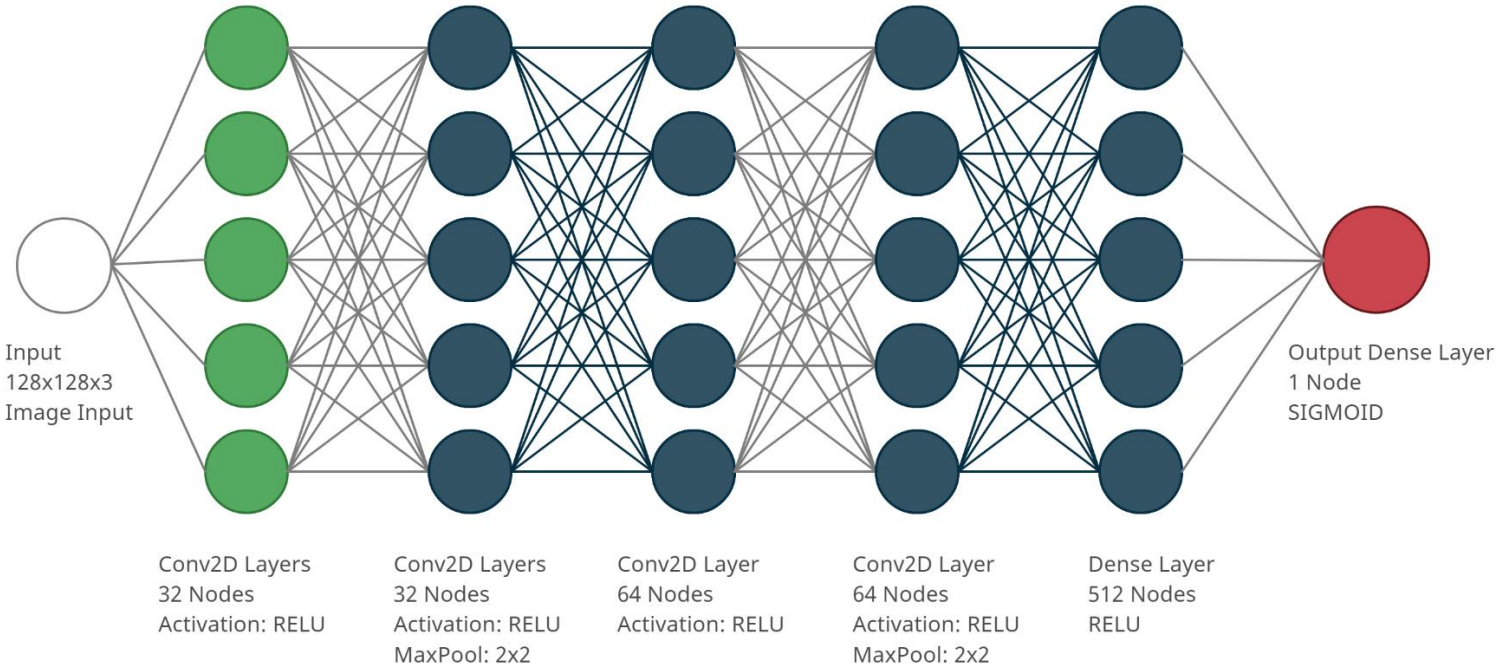

Fig. 3 The proposed convolutional neural network architecture.

Each input image had dimensions of 128 x 128 x 3 in jpeg or jpg format similar to Fig. 1 and Fig. 2 mentioned earlier. The proposed model was developed with one pathway having 4 convolutional layers and alternate max-pooling, A dense layer with 512 nodes to perform feature concatenation, A final dense layer that performs feature model classification and classifies whether image consists or doesn't consist a tumor.

In this approach, a preprocessed axial brain image of dimensions 128 x 128 x 3 pixels is taken as input. In the first layer of 32 nodes, a kernel of 3 x 3 slides through the image and applies the ReLU activation function on it. Hence, creating our first set of feature matrices. Then the image data enter the second layer of 32 nodes. Like the previous layer, a kernel of size 3 x 3 slides through the data and applies the ReLU activation function. The resultant image data undergoes batch normalization and then max pooling with pool size of 2 x 2. A dropout layer exists here to prevent overfitting.

After this, the data proceeds to the second set of convolutional layers. The third convolutional layer consists of 64 nodes. The kernel of size 3 x 3 slides over the resultant data from the previous layers while applying the ReLU activation layer. The resultant data then proceeds to the final convolutional layer also comprising of 64 nodes. The kernel size and the activation function remain the same as the previous layer. After this, the data again undergoes batch normalization and then max pooling with pool size of 2 x 2 and stride of 2 x 2. Another dropout layer is present here. The result is then flattened for the upcoming dense layer. All the features extracted in from the convolutions are then given individual weights in the dense layer of 512 nodes. The activation of this dense layer is ReLU. A final dense layer exists with 1 node and the Sigmoid activation. This will give us the percentage value of the accuracy of the prediction made by the model every time.

Table 1. Details of each layer, its output shape and parameters for CNN.

Layer	Output Shape	Parameters
Conv2D – 1 (32 Nodes)	(None, 128, 128, 32)	896
Conv2D – 2 (32 Nodes)	(None, 128, 128, 32)	9248
Batch Normalization – 1	(None, 128, 128, 32)	128
Max Pooling 2D – 1	(None, 64, 64, 32)	0

Dropout (25%)	(None, 64, 64, 32)	0
Conv2D – 3 (64 Nodes)	(None, 64, 64, 64)	18496
Conv2D – 4 (64 Nodes)	(None, 64, 64, 64)	36928
Batch Normalization – 2	(None, 64, 64, 64)	256
Max Pooling 2D – 2	(None, 32, 32, 64)	0
Dropout (25%)	(None, 32, 32, 64)	0
Flatten	(None, 65536)	33554944
Dense – 1 (512 Nodes)	(None, 512)	0
Dense – 2 (1 Node)	(None, 1)	513

In the proposed model, 33,621,409 params were applied wherein 33,621,217 were for trainable purpose and 192 were for non-trainable purpose. The proposed CNN has been implemented using TensorFlow. The number of trainable parameters were 33,621,217. The tests were performed in a Windows environment with an AMD Ryzen 5 CPU and an AMD RX 560X 4GB GPU. The training process took roughly 1 day and the average time to make one prediction is 0.1 secs.

2.3 Training and Performance

The proposed CNN underwent a cross validation technique with the slice train/test subgroups specified in the dataset as explained before. The model was trained for 35 epochs using the Adamax optimizer with a starting learning rate of 0.001 and beta_1 and beta_2 values as 0.9 and 0.999 respectively.

The model trained and validated around 3000 images in batch sizes of 32. The loss obtained was 0.0373 and the accuracy obtained was 0.9868. The validation loss obtained was 0.2695 and the validation accuracy was 0.9450. The graphs obtained for these are as shown in Fig 4 and Fig 5.

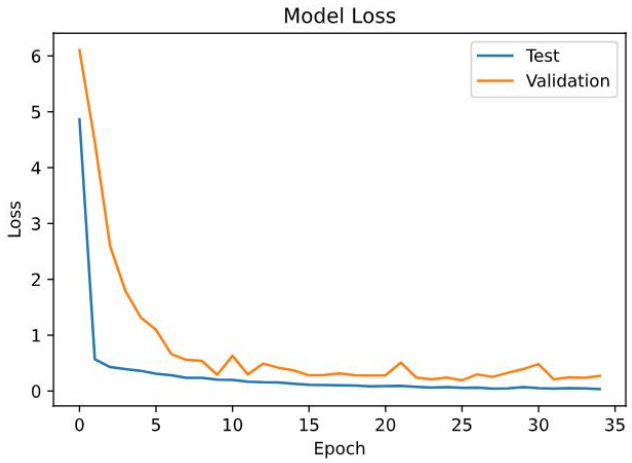

Fig. 4 Shows model loss throughout training

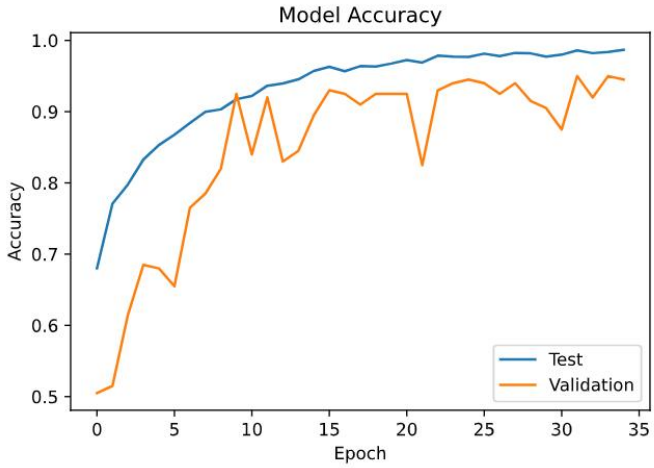

Fig. 5 Shows model accuracy throughout training

3. Results

On testing the model with new and previously unknow data, significantly high accuracy in prediction of tumors is clearly visible. The model trained and validated around 3000 images in batch sizes of 32. The loss obtained was 0.0373 and the accuracy obtained was 0.9868. The validation loss obtained was 0.2695 and the validation accuracy was 0.9450. The input and output images are shown in figures 6 and 7 respectively. It took 0.104 seconds to predict with an accuracy of 99.99 %. However, the images shown in figures 8 and 9 respectively took reasonably more time, that is 0.175 seconds with 100 % accuracy.

Furthermore, on acquiring all the feature matrices from the first layer till the last convolutional layer of the latest prediction, and stacking them one on top of the other, results in a 3D segmentation which clearly show the tumor.

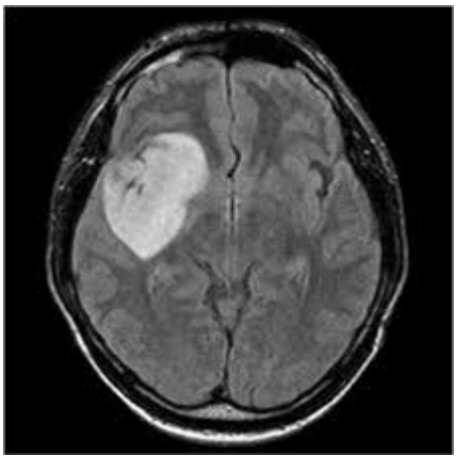

Fig. 6 Input Image

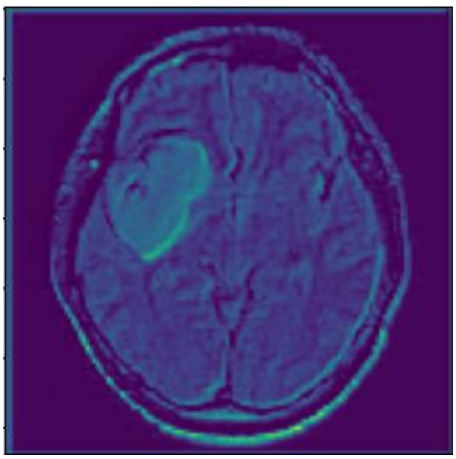

Fig. 7 Output Image

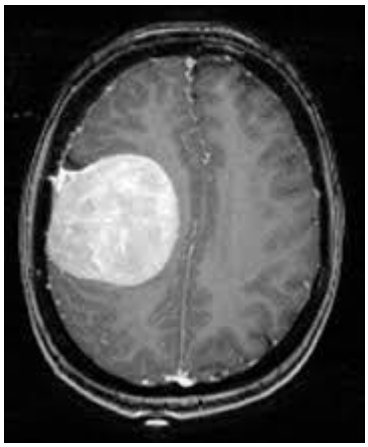

Fig (8): Input Image

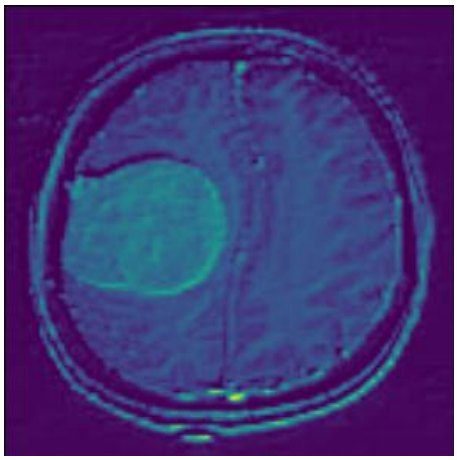

Fig (9): Output Image

Time taken for prediction: 0.175 seconds

Accuracy of current prediction: 100 %

4. Conclusion

A novel CNN architecture was presented in this study which can be used for automated brain tumor classification using MRIs. The classification was performed using an Axial MRI image database. As input, we used whole images, then preprocessed the images and went forth with identification and segmentation.

Our proposed neural network has outperformed classical models [8], it is simpler than classical pre-trained CNNs and can be executed on modern conventional PCs. The main reason being, our proposed approach utilizes fewer resources for training and testing purpose. It is always beneficial for developing countries to adapt models that require fewer resources, approaches that use smaller networks are preferable for such countries [7]. As in our proposed approach, due to less resource utilization, it can be deployed on mobile platforms as well.

The model trained and validated around 3000 images in batch sizes of 32. The loss obtained was 0.0373 and the accuracy obtained was 0.9868. The validation loss obtained was 0.2695 and the validation accuracy was 0.9450. In addition, the network has a very good execution speed of 0.1 seconds per image.

5. References

1. Bleyer, W. Archie. "Epidemiologic impact of children with brain tumors." *Child's nervous system* 15.11 (1999): 758-763.
2. Sharif, Muhammad Imran, et al. "A decision support system for multimodal brain tumor classification using deep learning." *Complex & Intelligent Systems* 8.4 (2022): 3007-3020.
3. Menze, Bjoern H., et al. "The multimodal brain tumor image segmentation benchmark (BRATS)." *IEEE transactions on medical imaging* 34.10 (2014): 1993-2024.
4. Badža, Milica M., and Marko Č. Barjaktarović. "Classification of brain tumors from MRI images using a convolutional neural network." *Applied Sciences* 10.6 (2020): 1999.
5. Ezhilarasi, R., and P. Varalakshmi. "Tumor detection in the brain using faster R-CNN." *2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), 2018 2nd International Conference on*. IEEE, 2018.
6. Abd-Ellah, Mahmoud Khaled, et al. "Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks." *EURASIP Journal on Image and Video Processing* 2018.1 (2018): 1-10.

7. Akram, M. Usman, and Anam Usman. "Computer aided system for brain tumor detection and segmentation." *International conference on Computer networks and information technology*. IEEE, 2011.
8. Díaz-Pernas, Francisco Javier, et al. "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network." *Healthcare*. Vol. 9. No. 2. MDPI, 2021.