Brain Tumor Classification and Segmentation Using Convolutional Neural Network From MRI images

*

Farsheed Rahman
Department of Computer Science and Engineering
Independent University, Bangladesh
Dhaka, Bangladesh
farsheedrahman@gmail.com

S.M. Arif Mahmud
Department of Computer Science and Engineering
Independent University, bangladesh
Dhaka, Bangladesh
smarifmahmud9@gmail.com

***Abstract*—Brain tumors are one of the most aggressive disease. They are caused when abnormal cells are formed and spreads from uncontrolled division of cells.They can be identified, classified and segmented using Convolutional Neural Networks in terms of medical image analysis. The study emphasizes the importance of accurate diagnosis and treatment planning in brain tumor management, facilitated by imaging techniques such as Magnetic Resonance Imaging (MRI). Using the power of CNNs, The research focuses on the classification and segmentation of brain tumors form raw MRI image, employing sophisticated algorithms and techniques. The methodology involves the utilization of U-Net architecture, know for its effectiveness in segmentation, to precisely outline brain tumors. The study uses two distinct datasets comprising a total of 3455 MRI images, sourced from Kaggle and curated by domain experts. Through rigorous experimentation and training, the CNN model demonstrates promising results in accurately identifying and classifying brain tumor. The training process involves dataset preprocessing, division into training, validation and testing sets, and optimization using the Adam optimizer. Evaluation metrics such as accuracy, loss curves, confusion matrices and Receiver Operating Characteristic (ROC) curve validate the effectiveness of the model without overfitting. The findings contribute to the growing body of knowledge in medical image processing offering a viable approach to enhance brain tumor detection and therapy.**

***Index Terms*—brain tumor, CNN,**

I. Introduction

Brain is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumor(1). Brain tumor are divided into two types such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor. Low grade brain tumor is called as benign. Similarly, the high grade tumor is also called as malignant. Benign tumor is not cancerous tumor. Hence it does not spread other parts of the brains.(2) However the malignant tumor is a cancerous tumor. So it spreads rapidly with indefinite boundaries to other region of the body easily. It leads to immediate death.

Imaging analysis is used for diagnosis, treatment planning, and the monitoring of patients. Magnetic Resonance Imaging (MRI) is a powerful non-invasive imaging technique for brain tumor assessment, providing high-resolution images with precise and minute anatomical details and tissue characterization.(3)

Over the past decades, significant discoveries have been made in the field of medical image analysis, particularly in the development of sophisticated algorithms and techniques for brain tumor classification and segmentation(4). These advancements have been primarily driven by the increasing availability of large-scale datasets, improvements in computational resources and advancements in machine learning and deep learning methodologies.(5)

The classification and segmentation of brain tumors involve several interconnected tasks, including image processing, feature extraction, and classification or segmentation.(6) Traditional machine learning techniques like support vector machines (SVMs) and random forests have been used for classification and segmentation.(7) However, with the creation of deep learning, convolutional neural networks (CNNs) have emerged as the main way for automatic future learning and classification or segmentation of brain tumors directly from raw MRI images.

This paper aims to use Convolutational Neural Network (CNN) to classify and segment brain tumors from MRI images.The dataset that have been used contains a total of 3264 MRI images to work from.The CNN will be trained to identify if there is a tumor or not and also classify and segment which type of tumor it is.

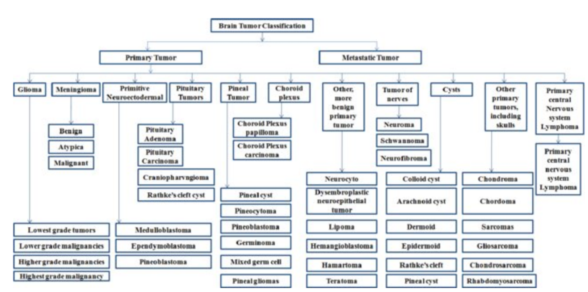

Fig. 1: Brain Tumor Classification According to AANS

II. METHODOLOGY

The human brain is modeled by using design and implementation of neural network. The neural network is mainly used for vector quantization, approximation, data clustering, pattern matching, optimization functions classification techniques. Neural network is divided into three types based on their interconnections. In the normal neural network, image cannot be scalable. But in convolution neural network, image can be scalable, that means that it can take 3D input volume to 3D output volume. The Convolution Neural Network(CNN) is a multilayer network that consists of input layer, convolution layer, Rectified Linear Unit layer, pooling layer and fully connected layer(8).

The input layer works as the entry point for data that goes into the network. Its primary function is to receive the input data and pass it on to the other layers for further processing. For Convolutional Neural Networks for brain tumor classification, the input layer accepts the raw image data and prepares it for feature extraction and classification. The convolutional layer detects and extracts features from the input data that are important for classification. After the operation is performed, an activation function, like a Rectified Linear Unit is applied to the output of the convolution operation. This gives non- linearity to the network, allowing it to learn complex relationships between input features and output predictions.

The human brain is modeled by using design and implementation of neural network. The neural network is mainly used for vector quantization, approximation, data clustering, pattern matching, optimization functions classification techniques. Neural network is divided into three types based on their interconnections. In the normal neural network, image cannot be scalable. But in convolution neural network, image can be scalable, that means that it can take 3D input volume to 3D output volume. The Convolution Neural Network(CNN) is a multilayer network that consists of input layer, convolution layer, Rectified Linear Unit layer, pooling layer and fully connected layer. The input layer works as the entry point for data that goes into the network. Its primary function is to receive the input data and pass it on to the other layers for further processing. For Convolutional Neural Networks for brain tumor classification, the input layer accepts the raw image data and prepares it for feature extraction and classification. The convolutional layer detects and extracts features from the input data that are important for classification. After the operation is performed, an activation function, like a Rectified Linear Unit is applied to the output of the convolution operation. This gives non- linearity to the network, allowing it to learn complex relationships between input features and output predictions.

In some cases, after applying convolution, the pooling layer comes into play. This layer performs spatial downsampling by partitioning the input feature map into non-overlapping regions and then reducing each region to a single value. This effectively decreases the spatial resolution of the feature map while still having the most important information. There are different types of pooling layers, with max-pooling and average-pooling being the most common. Then the flatter layer prepares the data for input into the fully connected layer. The fully connected layer combines the extracted features to make a final decision about the presence of a brain tumor. Dropout regularization is applied to reduce overfitting by randomly dropping out connections during training.

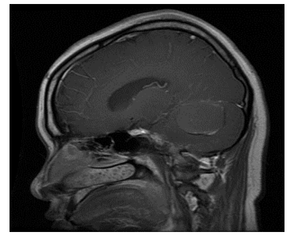

Fig. 2: Glioma Tumor

A. *Dataset*

Two datasets are used for the identification,classification and segmentation. The dataset that is used for identification contains brain images collected through MRI scans. The datasets contains 3264 MRI divided into four subfolders.They are lso divided into two subsubfolders that are training and testing They are divide into glionoma tumor, meningioma tumor, no tumor, and pituitary tumor. The glionoma tumor folder contains 826(Train) + 100(Test) images, the meningioma tumor contains 822(Training) + 115(Testing), the no tumor contains 395(Training) + 105(Testing) and the pituitary tumor contains 827(Training) + 74(Testing). The dataset is obtained from Kaggle and is made by Shivam Agarwal, a student at AICTE.

B. *Network Architecture*

The network architecture that is used for the brain tumor classification is U-Net. This architecture has proven effective

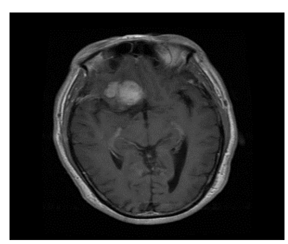

Fig. 3: Meningioma Tumor

Fig. 4: Pituitary Tumor

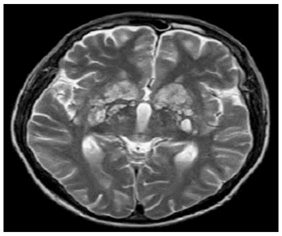

Fig. 5: No Tumor

for semantic segmentation because its ability to precise localization and delineation of tumor regions which are crucial for segmentation. The architecture contains layers through which the input goes through for precise segmentation and classification. The layers and their working are in the following

1) Input Layer: This is the layer where the inputs are entered and they are then subsequently passed onto the other layers form further processing. For this model, the inputs are MRI images, totaling 3264, that are obtained from the two datasets. The data that is received, in this case, images contains pixels which are arranged in a grid-like structure. The inputs of the images are (150,150,3). These represent the height and width of the images. The 3 is the color channels. Preprocessing steps are also undertaken in this layer. The images are resized to enhanced performance and suitability for further usage by the network. Once the data is shaped and preprocessed, it is passed on to the next layer in the network.

2) Convolutional Layer: This layer is a fundamental building block of the Convolutional Neural Networks(CNNs) and is the layer where feature extraction is done. They normally detect features such as edges, textures, pattern and other visual elements in the case of image data. Then convolution operation are applied to the input data using filters and kernels. Filters are small, square- shaped matrices that slide across the input data, calculating dot products at each position. This helps in detecting pattern and features. The 2D convolutional layer contains 32 filters each with a kernel size of (3,3), with a stride of 1, and a Rectified Linear Unit, which is activation function, which is applied so that it can learn non-linearity.This helps it to learn complex relationships between input features and output predictions. Another 2D convolutional layer is added with 64 filters and a 3x3 kernel size.

3) Pooling Layer : This layer is mainly used to reduce the spatial dimensions of the feature maps therefore reducing the computational complexity of the network and controlling overfitting. Max-Pooling is used for the data that is provided. The default pool size is (2,2), which downsamples the input by taking the maximun value over a 2x2 window. The stride is 1. The same patter of adding convolutional and max pooling layers is repeated twice more, gradually increasing the number of filters to 32 and then reducing back to 16. A dropout layer is add with a rate of 0.3 to prevent overfitting.

4) Flatten Layer: This layer serves a critical role as it transforms the multi-dimensional output into one-dimensional array. This is necessary as the fully connected layers only requires one-dimensional outputs.

5) Dense Layer: Dense layer or the fully connected layer is a fundamental component where neurons are added. Here, every neuron is connected to every layer in the previous layer. Acticvation function are also utilized. Here, at first, 512 neurons and ReLU are added .Another dropout layer is added to prevent overfitting. Then another dense layer is added with a single neuron and sigmold activation function is added as output layer for binary classification task.

6) Output Layer: This is the final layer that is responsible for producing the outputs based on the features extracted from the input data. The neurons in the output layers matches the classes in the dataset so 4 neurons are added with a softmax activation function. The activation function outputs probabilities representing the likelihood of each class.

C. Training Strategy

Training in the context of neural networks, refers to the process of adjusting the parameters of the model using a training dataset to minimize the loss function. Its objective is to teach the model to make accurate predictions or classifications based on the input data. For a model to train some procedures must be followed. At first, the dataset that is used must loaded must be used. Some preprocessing is done so that can be used suitably in the network.

Then the datasets are split into three subsets: training, validation and testing sets. The training set is used to train the model, the validation set is used to adjust the hyperparameters and monitor the model's performance during training, and the testing set is used to evaluate the final performance of the trained model. For the two datasets that are used in the model, they have been split into three subsections. The training set contains 70 percent of the images, the validation set contains 20 percent of the images and the testing set contains 10 percent of the images. Both of the datasets are divided in this format.

After going through the layers of the CNN model, it is compiled using the Adam optimizer. This is used to minimize the loss function during training. Here the evaluation metrics such accuracy, loss and the confusion matrix, that are going to be calculated are stated. Then the compiled model is trained. The model is trained for 20 epochs. For each epoch, it went through approximately 83 steps per epoch with each step processing a batch of data of 32.

After the training, the testing dataset is used to evaluate the trained model. Based on the evaluations, the accuracy curve, loss curve and the confusion metrics are calculated. This metrics helps to assess its effectiveness of its given task.

III. Results And Analysis

After developing and training the CNN model its is optimized using the Adam optimizer. This is used to minimize the loss of the loss function. Then the accuracy and the loss data are calculated. Fig 2 and 3 shows the loss curve. The training loss curve for both the datasets are decreasing which confirms that the model is training to make better predictions. The validation loss curve must decrease simultaneously with the training and it is doing so. This shows that the model is not overfitting and is likely generalizing with the validation set.The accuracy curve is shown in Fig 4 and 5 . It also shows that the training accuracy is increasing and the validation loss is increasing simultaneously which indicated the the model is getting better at predicting and also not overfitting.

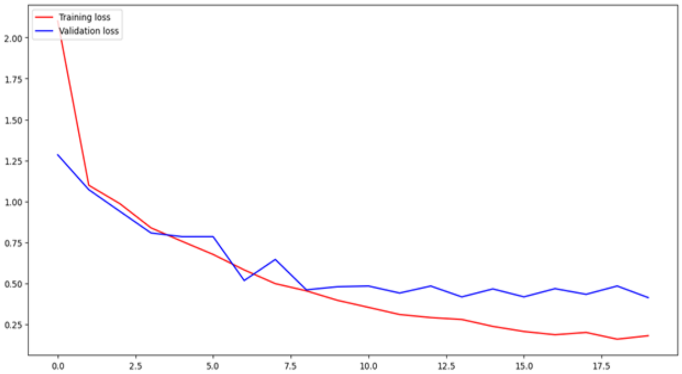

Fig. 6: Accuracy Curve For Classification

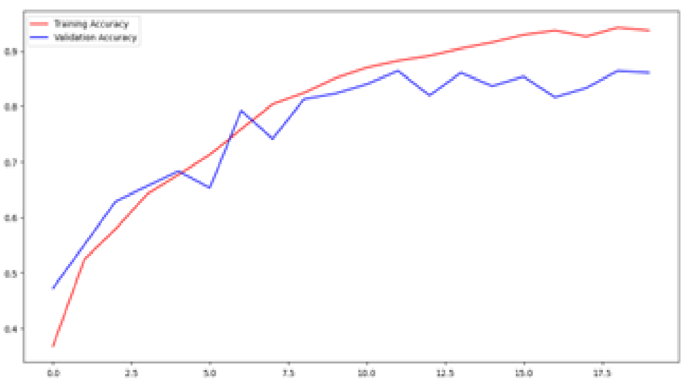

Fig. 7: Loss Curve For Classification

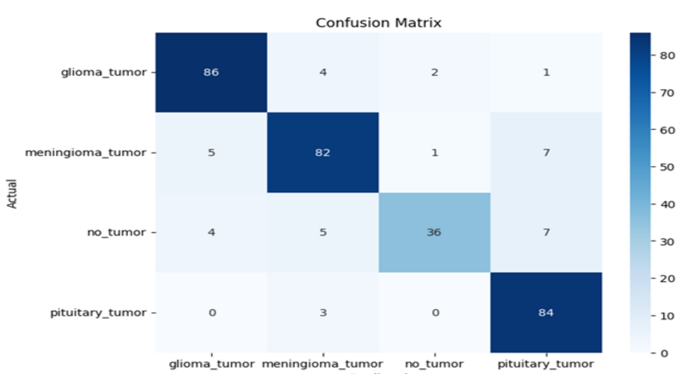

Fig. 8: Confusion Matrix for Classification

Fig 6 shows the confusion matrix. This provides a comprehensive summary of the performance of a classification model by presenting the counts of true positive, true negative, false negative and false positive predictions for each class in the

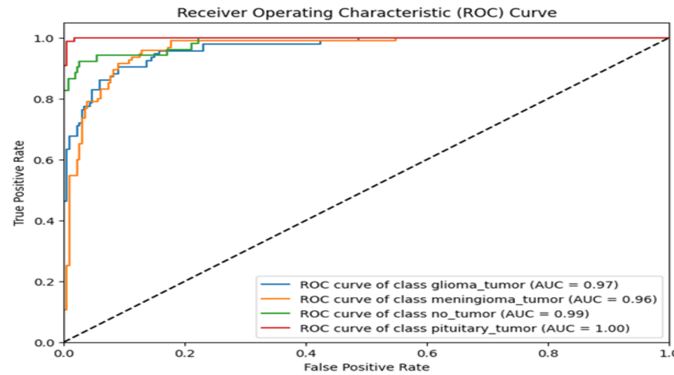

Fig. 9: ROC Curve for Classification

dataset. By analyzing the confusion matrix, it is confirmed that the model is accurate. A ROC curve was also calculated from the data.As the curve hugs the top left hand corner, it means that the model is performing well as it achieves higher true positive rates(TPRs) with lower False Positive Rate(FPRs). The Area under the Curve (AUC)) is nearer to 1 for all of the class, so it indicates a better performance of the model.

IV. Conclusion

This research emphasizes the crucial relevance of modern machine learning approaches of medical imaging analysis, based on a thorough investigation of brain tumor classification and segmentation using Convolutional Neural Networks(CNNs). We have shown that a model can effectively identify and classify brain tumours from MRI images by developing and optimizing the model.

Our approach makes use of CNNs, which are highly effective in deriving intricate patterns and features from unprocessed picture data. By utilizing multiple layers including convolutional, pooling and fully connected layers, our model effectively extracted meaningful features from MRI images and made predictions with high accuracy.

The results and analysis demonstrate the successful training and validation of the CNN model, showcasing decreasing loss curves and increasing accuracy curves, indicating the model's ability to generalize well to unseen data without overfitting. Additionally, the confusion matrix provides a comprehensive overview of the model's performance, confirming its accuracy in classifying brain tumors.

All things considered, this study adds to the expanding body of knowledge in medical image processing and offers a viable method for improving brain tumor detection and therapy. In the future, patients and medical professionals alike may benefit from increased performance and wider application of CNN models in clinical settings as a result of additional improvements and validations of these models.

References

[1] J. Seetha and S. Selvakumar Raja, "Brain tumor classification using convolutional neural networks," *Biomedical and Pharmacology Journal*, vol. 11, no. 3, p. 1457, 2018.

[2] N. Abiwinanda *et al.*, "Brain tumor classification using convolutional neural network," vol. 1, 2019.
[3] S. Das, O. R. Rahman Aranya, and N. N. Labiba, "Brain tumor classification using convolutional neural network," 2019.
[4] S. M. Kulkarni and G. Sundari, "A framework for brain tumor segmentation and classification using deep learning algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 8, 2020.
[5] A. İşın, C. Direkoğlu, and M. Şah, "Review of mri-based brain tumor image segmentation using deep learning methods," *Procedia Computer Science*, vol. 102, pp. 317–324, 2016.
[6] S. Pereira *et al.*, "Brain tumor segmentation using convolutional neural networks in mri images," *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.
[7] M. H. O. Rashid *et al.*, "Brain tumor detection using anisotropic filtering, svm classifier and morphological operation from mr images," 2018.
[8] T. Liu *et al.*, "Implementation of training convolutional neural networks," *arXiv preprint arXiv:1506.01195*, 2015.