

Brain Tumor MRI analysis using Deep Convolution Neural Network with Optimization Framework

Mrs. C. P. Jetlin¹, Dr. L. Sherly Pushpa Annabel²

Submitted: 22/07/2022 Accepted: 25/09/2022

Abstract: Analysis of Brain Tumor plays predominant role in detecting the tumor cells of the brain. At its most advanced stages, a brain tumor can be extremely fatal. It can quickly travel to other sections of the brain and harm healthy brain cells due to its uncontrollable reproduction. As a result, early detection is critical in the treatment of patients with the goal of increasing their life expectancy. However, because tumors have complicated characteristics in terms of appearance and limits, detecting them is a difficult and demanding task. For the diagnosis of brain cancers, magnetic resonance imaging (MRI) is widely employed, which necessitates segmenting large volumes of 3D MRI images, which is difficult to do manually. A modified version of VGG16 CNN and a sequential model were proposed for the automatic segmentation and detection of a brain tumor utilizing MRI images in this system. The suggested CNN model is compared to AlexNet, ResNet-50, VGG-16, and GoogleNet, which are all popular functional CNN models. Using 1030 brain MRI scans, it is able to achieve an overall accuracy of 98 percent and a cross entropy of 0.097. Using the Adam optimization approach, all of the key hyper parameters of CNN models are automatically designated. The proposed CNN models can be used to help physicians and radiologists validate their initial brain tumour screening with high accuracy and efficiency.

Keywords: Brain tumor, Magnetic resonance Imaging (MRI), Convolution Neural Network (CNN), Keras

1. Introduction

Tumor is a fibrous web of undesired tissue growth that proliferates uncontrollably inside our brain. Malignant tumor cells are aberrant cells that multiply uncontrollably and irregularly. Normal tissues can be compressed, infiltrated, or destroyed by these tumors. Unlike benign tumors in other organs, benign tumors in the brain can sometimes be life threatening. Many fields, such as the diagnosis of various stages of tumors in hospitals and clinics, rely on brain tumor analysis. They're mostly employed for medical research and analysis. Because of the Deep Learning approach, the quantity of MRI brain pictures required for analysis has increased significantly. Traditional computer approaches may be able to detect the tumor, but they are not always reliable. It lacks sturdiness despite contemporary medical technological developments, histological evaluation of biopsy specimens is still used to diagnose, classify, and grade brain cancers.

Clinical examination and interpretation of imaging modalities such as magnetic resonance imaging (MRI) or Computed Tomography (CT) are frequently followed by pathological testing to arrive at a definitive diagnosis. The

most well-known drawbacks of this diagnostic procedure are that it is invasive, time-consuming, and prone to sampling errors. It is possible to improve physicians' and radiologists' diagnostic abilities and reduce the time required for a right diagnosis with the use of computer-aided completely automated detection and diagnosis systems that aim to make fast and accurate judgments by specialists.

The goal of this research is to create a reliable system that can accurately detect brain tumors. A total of 1,030 photos, including tumor and non-tumor images, were used in the experiment to locate brain tumors in various locations and under varied conditions. The Bilinear interpolation technique, which is used to resize the image in preprocessing, is used to remove undesired noise and distortions inside the image. To remove the undesirable noise in this photograph, Gaussian blur was used. The classifier we'll use is straightforward to set up, robust to noisy training data, and successful when dealing with big amounts of data. As a result, it is regarded as one of the most effective classifiers for identifying the various stages of a brain tumor. Rectified Linear Unit is the activation function that we will utilise (ReLU). Following the completion of the classification module, the next step is to undertake the segmentation procedure, which entails the use of various morphological techniques to segment the images.

¹ Research Scholar, Jerusalem College of Engineering, Anna University, Chennai, India.

ORCID ID : 0000-0001-8346-991X

² Professor, Department of Computer Science and Engineering St. Joseph's College of Engineering, Chennai, India.

Email id: jetpear@gmail.com

The U-Net Architecture is used to segment the data. It does image segmentation and produces better results than other segmentation methods. It's particularly useful for segmentation jobs because it can locate effectively and generate high-resolution segmentation masks. The following is how the rest of the paper is structured: Section 2 includes a summary of relevant studies as well as a full analysis of these investigations. The thorough analysis of the dataset used is described in Section 3. Section 4 delves into the proposed CNN models in further depth. Sect. 5 contains the findings of the experiments. Section 6 specifies conclusion and future enhancement of this paper.

2. Related Work

In this section, we've looked at a few studies that show how deep learning is linked to the Brain Tumor Analysis system. "Efficient MRI segmentation and detection of brain tumor using convolution neural network," proposed Alpana Jijja et al.[1] It created an automated system for brain tumor segmentation and detection. It employed the WCA optimization technique to cluster the photos in the most efficient way possible. "Efficient brain tumor segmentation multi scale two-pathway—group convolution neural network," proposed Muhammad Imran et al. [2]. It used two pathway group CNN to propose a fully automatic brain tumor segmentation technique. Hossam H.sultan, Nancy M. Salem, and Walid al-atabany [3] reported a CAD system for the classification of brain tumor MR images in "Multi categorization of brain tumor images using deep neural network." Sanjay M.Shelke et al. [4] suggested "Automatic segmentation and detection of brain tumor using MRI," which can be utilized to make an early diagnosis and monitor the tumor.

Liya Zhao et al. [5] presented "Multiscale CNN's for brain tumor segmentation and diagnosis," but it can only accommodate fixed-size input pictures and is hence not optimum. Mzoughi et al.[6] proposed a deep multi-scale 3D CNN model for grading brain tumors based on volumetric 3D MRI images. The proposed method correctly classified low-grade glioma and high-grade glioma brain tumor images with 96.49 percent accuracy. Cinar et al. [7] employed a modified version of the pre-trained ResNet-50 CNN model for brain tumor identification, replacing the last 5 layers with 8 new layers. With this improved CNN model, they were able to obtain 97.2 percent accuracy utilizing MRI scans. Mohsen et al. (2018) [8] classified brain MRI images into four categories: normal brain, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors using a deep neural network (DNN) classifier paired with discrete wavelet transform (DWT) and principal component analysis (PCA). The accuracy percentage was discovered to be 96.97%. Kabir Anaraki et al. [9] proposed using MRI scans to classify different types of glioma using a CNN

and genetic algorithm (GA)-based technique. They classified three glioma grades with 90.9 percent accuracy and glioma, meningioma, and pituitary tumor types with 94.2 percent accuracy.

3. Datasets

There aren't a lot of brain picture datasets accessible. As a result, the datasets are manually collected at various locations, such as clinics and other medical institutes. Images of the brain with tumors are collected and saved as part of the dataset. We have approximately 1,030 photos of brains in various viewpoints, some of which have tumors and others do not. When data is acquired, varied lighting, circumstances, and images of the brain are observed and collected, such as images of the brain at light and dark intensities. Some of the pictures are obtained through NBIA Archieve, while others are obtained directly from medical institutions. The images are separated into two categories: tumor and non-tumor brain images. Training and testing sets are created for further processing based on the segregation. Because we're employing deep learning techniques, the dataset required for processing is quite large. As a result, big datasets are required to implement deep learning techniques.

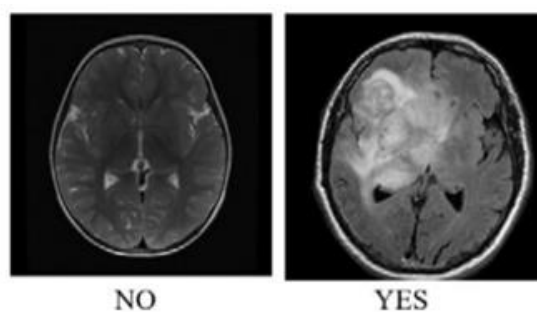


Fig 1: Sample Brain Image

4. Convolution Neural Network

The objective of this paper is to construct fully automatic CNN modified sequential and VGG models for brain tumour multi-classification utilising MRI images. For easier processing, the images will be transformed to grey scale. The image's contrast will then be saturated using Morphological processing techniques. In pre-processing, bilinear interpolation is the interpolation technique used to resize the image. After that, the image is smoothed with a Gaussian blur.

To smooth the image, another morphological filter will be used to remove tiny noise. Grid search optimization automatically tunes important hyper-parameters of CNN models. The first of these CNN models is used to detect brain tumours, and so determines whether or not a given MRI image of a patient contains a tumour. The adam optimization approach and binary cross entropy loss

function are used to construct the model. By giving the training and validation photos, the model is created and trained. The model is then tested using the test image set after it has been trained. The same dataset is then fed into the CNN algorithm. Rectified Linear Unit was the activation function we used (ReLU).

4.1 Algorithm Proposed

```

classifier = functional1()
classifier.add(Conv2D(32, (3, 3), input_shape=(224, 224, 3),
activation='relu'))
classifier.add(MaxPooling2D(pool_size=(2, 2)))
classifier.add(Conv2D(32, (3, 3), activation='relu'))
classifier.add(MaxPooling2D(pool_size=(2, 2)))
classifier.add(Flatten())

```



Fig 2: CNN Model

Adam optimization automatically tunes important hyper-parameters of CNN models. The first of these CNN models is used to detect brain tumors; as a result, it determines whether or not a patient's MRI image has a tumour.

In this paper, the accuracy and reliability of the classification process are measured using these measures, which are widely acknowledged as standard performance evaluation metrics in image classification investigations. Furthermore, the area of the receiver operation characteristic curve (ROC), also known as the AUC of ROC curve, is used to assess the models' performance.

Eq. 1 shows the corresponding formulas for each of these measures. True positive, true negative, false positive, and false negative are the letters TP, TN, FP, and FN, respectively.

$$\begin{aligned}
 \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\
 \text{Specificity} &= \frac{TN}{TN + FP} \\
 \text{Sensitivity} &= \frac{TP}{TP + FN} \\
 \text{Precision} &= \frac{TP}{TP + FP}
 \end{aligned}
 \tag{1}$$

Table 1: Performance Evaluation

```

classifier.add(Dense(units=128, activation='relu'))
classifier.add(Dense(units=2, activation='sigmoid'))

```

The U- Net Architecture is used to segment the data. It does image segmentation and produces better results than other segmentation methods. It excels in segmentation tasks due to its ability to locate well and produce high-resolution segmentation masks. Because the training data is expressed in terms of the number of patches within a picture, which is far bigger than the number of coaching photos, it performs well with tiny datasets and is somewhat resistant to over fitting.

As illustrated in Fig. 2, the proposed CNN model for Classification consists of 13 weighted layers (1 input, 2 convolutions, 2 ReLU, 1 normalisation, 2 max pooling, 2 fully connected, 1 dropout, 1 softmax, and 1 classification layers) as shown below

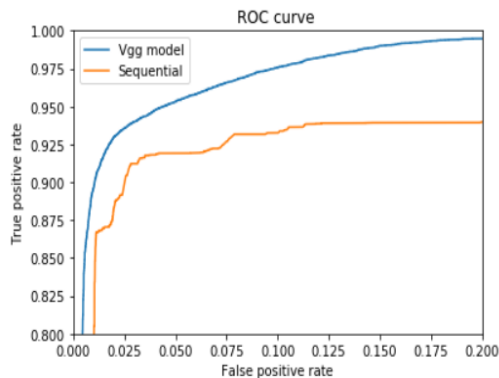


Fig 3: ROC Curve- Proposed Model

5. Experiment and Result

We have developed the CNN model in keras with tensorflow as backend. It has been trained with medical tumor dataset with 1,030 images. Here the training and validation accuracy will be considered. Because there are 1,030 options to be checked with the fivefold cross-validation technique, the grid search algorithm meant to optimize the architectural hyper-parameters of the CNN model is conducted a total of 11,200 times. Similarly, to achieve the best accuracy, four parameters must be tuned.

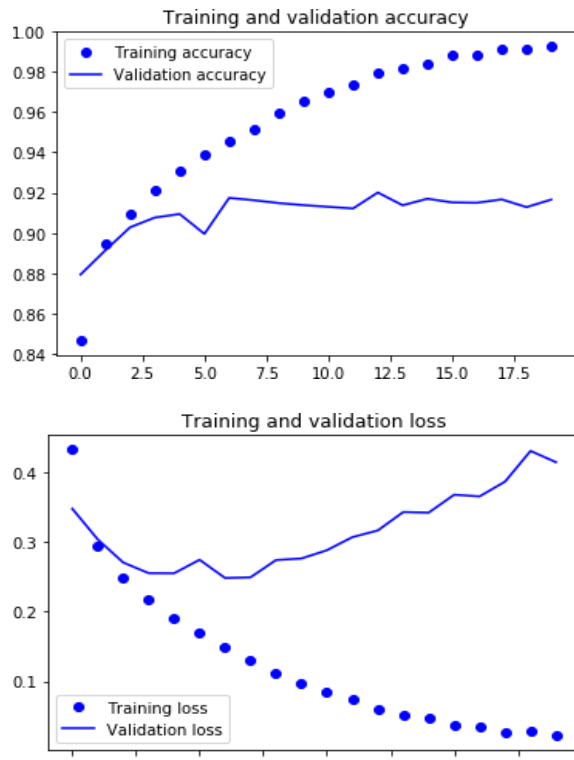


Fig 4: Training and Validation Accuracy with Loss

For the Classification 1 task, the suggested model's performance is assessed using a fivefold cross-validation approach.

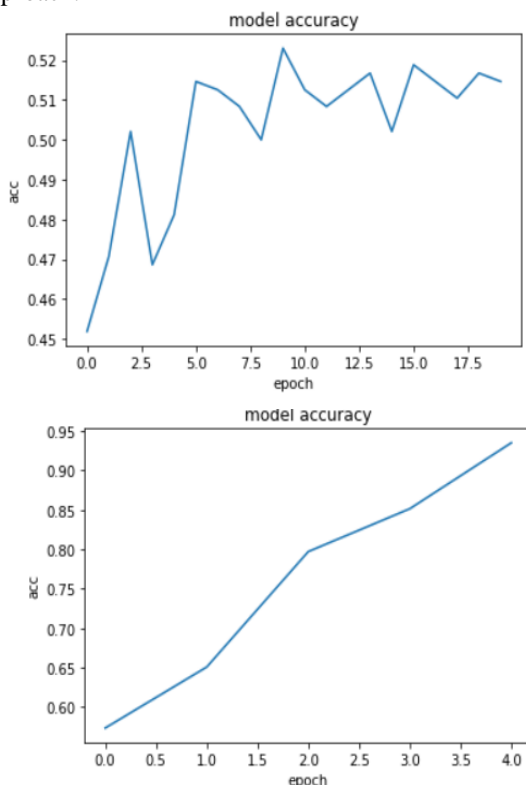


Fig 5: CNN Model Accuracy

The dataset is separated into five sets, with four sets used for training and the fifth set used for testing. Five times the experiments are carried out. The task's classification performance is evaluated for each fold, and the model's

average classification performance is determined. Without testing the trained and hyper-parameter-tuned CNN on predicting unknown samples, high accuracies from the training and validation phases are meaningless. The model accuracy for modified sequential and VGG model is given above

6. Future Work and Conclusion

The proposed CNN models' performs well with those of existing popular state-of-the-art CNN models. The same tests are carried out with the same dataset using well-known pre-trained CNN models such as AlexNet, Inceptionv3, ResNet-50, VGG-16, and GoogleNet. The accuracy and AUC acquired throughout the experiments are compared between the proposed CNN models and some popular networks. An automated brain tumor analysis system that will be beneficial in a variety of settings. A key feature of our system is that we have used the CNN model, which is used not only for detection but also for segmentation. The neural network is the most efficient part. In a Deep Neural Network, the UNet performs an important part in our system. The proposed strategy is a beneficial diagnosing technique for physicians to detect brain cancers, according to research and analysis. It would be interesting to include more feature details in future development. Following the same line of research provided here, it will be intriguing to continue constructing more adaptive models for various forms of brain tumours. The detection of tiny malignant brain tumours is another prospective field of research.

References

- [1] Alpana Jijja and Dr. Dinesh Rai "Efficient MRI segmentation and detection of brain tumor using convolutional neural network". International Journal of Advanced Computer Science and Applications, Volume. 10, No. 4, 2019.INSPEC Accession Number: 17316117.
- [2] Meneses, B., E. L. Huamani, M. Yauri-Machaca, J. Meneses-Claudio, and R. Perez-Siguas. "Authentication and Anti-Duplication Security System for Visa and MasterCard Cards". International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 7, July 2022, pp. 01-05, doi:10.17762/ijritcc.v10i7.5558.
- [3] Muhammad Imran Razzak, Muhammad Imran, Guandong Xu proposed "Efficient brain tumor segmentation multiscale two-pathway—group convolutional neural network. DOI 10.1109/JBHI.2018.2874033, IEEE Journal of Biomedical and Health Informatics vol. 6, no. 1, January 2007.
- [4] Hossam H.sultan , Nancy M. salem , and walid al-atabany "Multi classification of brain tumor images using deep neural network" IEEE Journal Received April 25, 2019, accepted May 16, 2019, date of publication May 27, 2019, current version date is June

7, 2019. Digital Object Identifier 10.1109/ACCESS.2019.2919122.

- [5] Chauhan, T., and S. Sonawane. "The Contemplation of Explainable Artificial Intelligence Techniques: Model Interpretation Using Explainable AI". *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 4, Apr. 2022, pp. 65-71, doi:10.17762/ijritcc.v10i4.5538.
- [6] Sanjay M. Shelke and Sharad W. Mohod "Automatic segmentation and detection of brain tumor from MRI " *IEEE Journal* 2018 978-1-5386-5314-2/18/\$31.00 ©2018 IEEE.
- [7] Liya Zhao and Kebin Jia proposed "Multiscale CNN's for brain tumor segmentation and diagnosis" *International Journal of Engineering and Technology* - February 2019 Volume 2016, Article ID 8356294, DOI: 10.21817/ijet/2019/v11i1/191101022.
- [8] Yi Ding 1,2, Chang Li 1, Qiqi Yang 1, Zhen Qin 1, Zhiguang Qin "How to improve the deep residual network to segment multi-modal brain tumor images" DOI 10.1109/ACCESS.2019.2948120, IEEE Access.
- [9] Nouby M. Ghazaly, A. H. H. . (2022). A Review of Using Natural Gas in Internal Combustion Engines. *International Journal on Recent Technologies in Mechanical and Electrical Engineering*, 9(2), 07–12. <https://doi.org/10.17762/ijrmee.v9i2.365>
- [10] C, inar A, Yildirim M (2020) Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. *Med Hypotheses* 139:109684.
- [11] Mohsen H, El-Dahshan ESA, El-Horbaty ESM, Salem ABM (2018) Classification using deep learning neural networks for brain tumors. *Future Comput Informat J* 3(1):68–71.
- [12] Kabir Anaraki A, Ayati M, Kazemi F (2019) Magnetic Resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms. *Biocybern Biomed Eng* 39(1):63–74.
- [13] Malla, S., M. J. . Meena, O. . Reddy, R, V. . Mahalakshmi, and A. . Balobaid. "A Study on Fish Classification Techniques Using Convolutional Neural Networks on Highly Challenged Underwater Images". *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 4, Apr. 2022, pp. 01-09, doi:10.17762/ijritcc.v10i4.5524.
- [14] Premananda Sahu, Satyasis Mishra, Tadesse Hailu Ayane, T. Gopi Krishna, Ellappan Venugopal, Harish Kalla "Detection and Classification of Brain tumor tissues from Noisy MR Images using hybrid ACO-SA based LLRBFNN model and modified FLIFCM algorithm " ,2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP) 978-1-5386-7989-0/19/\$31.00 ©2019 IEEE.
- [15] Dr. N. Poonguzhali, Ms. Kagne Raveena Rajendra, Ms. T. Mageswari, Ms. T. Pavithra Heterogeneous Deep Neural Network for Healthcare Using Metric Learning, *Proceeding of international conference on systems omputation automation and networking 2019 @IEEE* 978- 1-7281-1524-5.
- [16] L. N. Balai, G. K. J. A. K. S. (2022). Investigations on PAPR and SER Performance Analysis of OFDMA and SCFDMA under Different Channels. *International Journal on Recent Technologies in Mechanical and Electrical Engineering*, 9(5), 28–35. <https://doi.org/10.17762/ijrmee.v9i5.371>
- [17] S. Cui, L. Mao and S. Xiong, "Brain tumor automatic segmentation using fully convolutional Networks", *Journal of Medical Imaging and Health Informatics*, vol. 7, no. 7, pp. 1641-1647, 2017.
- [18] Mustaqeem, A. Javed and T. Fatima, "An efficient brain tumor detection algorithm using watershed & thresholding-based segmentation", *International Journal of Image, Graphics and Signal Processing*, vol. 4, no. 10, pp. 34-39, 2012.
- [19] V. Padole and D.S. Chaudhari, "Detection of the brain tumor in MRI images using the mean shift[MS] algorithm and normalized cut method", *International journal of Engineering and Advanced Technology* pp. 52-56, 2012.
- [20]. Baes, A. M. M. ., Adoptante, A. J. M. ., Catilo, J. C. A. ., Lucero, P. K. L. ., Peralta, J. F. P., & de Ocampo, A. L. P. (2022). A Novel Screening Tool System for Depressive Disorders using Social Media and Artificial Neural Network. *International Journal of Intelligent Systems and Applications in Engineering*, 10(1), 116–121. <https://doi.org/10.18201/ijisae.2022.274>
- [21] S. Roy and S. Bandyopadhyay, "Detection and quantification of brain tumor from MRI of brain and it's symmetric analysis", *International Journal of Information and Communication Technology Research (IJICTR)* volume. 2, no. 6, pp. 477-483, 2012. Accessed on 30 March 2019.
- [22] S. Cui, L. Mao and S. Xiong, "Brain tumor automatic segmentation using fully convolutional Networks", *Journal of Medical Imaging and Health Informatics*, vol. 7, no. 7, pp. 1641-1647, 2017.
- [23]. Gupta, D. J. . (2022). A Study on Various Cloud Computing Technologies, Implementation Process, Categories and Application Use in Organisation. *International Journal on Future Revolution in Computer Science & Communication Engineering*, 8(1), 09–12. <https://doi.org/10.17762/ijfrcsce.v8i1.2064>
- [24] A. Kaur, "An automatic brain tumor extraction system using different segmentation methods," *Second International Conference on Computational Intelligence & Communication Technology (CICT)*, 2016.
- [25] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. H. Tang, H. Lu, W. Liu, and X. Tao, "Tumor segmentation from contrast MRI images of brain," *twelfth IEEE International Symposium on Biomedical Imaging (ISBI)*, 2015.
- [26] E. El-Dahshan, H. Mohsen, K. Revett and M. Salem, "Computer-aided diagnosis of brain tumor through MRI- A survey and a new algorithm", *Expert Systems with Applications* volume. 41, no. 11, pp. 5526-5545, 2014. Available: 10.1016/j.eswa.2014.01.021.