SHODH SAMAGAM

ISSN : 2581-6918 (Online), 2582-1792 (PRINT)

VGG-16 Convolutional Neural Networks For Brain Tumour Detection

Snehlata Mandal, Department of Computer Science and Engineering,
Ashutosh Pradhan, Shubham Vishwakarma, B.Tech 7th semester, CSE Branch,
Shri Shankaracharya Group of Institutions, Bhilai, Chhattisgarh, India

ORIGINAL ARTICLE

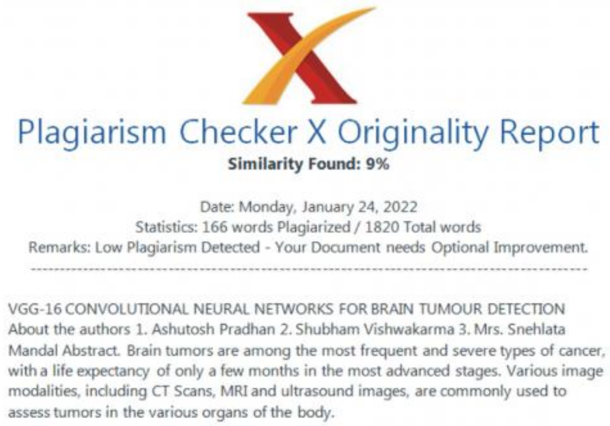


Corresponding Authors

Snehlata Mandal, Department of Computer Science and Engineering,
Ashutosh Pradhan, Shubham Vishwakarma, B.Tech 7th semester, CSE Branch,
Shri Shankaracharya Group of Institutions,
Bhilai, Chhattisgarh, India

shodhsamagam1@gmail.com

Received on : 22/01/2022
Revised on : -----
Accepted on : 29/01/2022
Plagiarism : 09% on 24/01/2022



Plagiarism Checker X Originality Report
Similarity Found: 9%

Date: Monday, January 24, 2022
Statistics: 166 words Plagiarized / 1820 Total words
Remarks: Low Plagiarism Detected - Your Document needs Optional Improvement.

VGG-16 CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN TUMOUR DETECTION About the authors 1. Ashutosh Pradhan 2. Shubham Vishwakarma 3. Mrs. Snehlata Mandal Abstract. Brain tumors are among the most frequent and severe types of cancer, with a life expectancy of only a few months in the most advanced stages. Various image modalities, including CT Scans, MRI and ultrasound images, are commonly used to assess tumors in the various organs of the body.

ABSTRACT

Brain tumors are among the most frequent and severe types of cancer, with a life expectancy of only a few months in the most advanced stages. Various image modalities, including CT Scans, MRI and ultrasound images, are commonly used to assess tumors in the various organs of the body. However, such huge amounts of data presented by these image scanning techniques poses a difficulty in analyzing them manually and requires a lot of human effort. Convolutional neural networks (CNNs) have been shown to outperform standard methods when it comes to classifying brain tumor. In this model, we provide a completely automated computerized system for brain tumor categorization that employs optimal deep features from a variety of well-known CNNs and abstraction levels. We use Transfer Learning from ImageNet for optimized feature training. VGG-16 is architecture is used with modification to its number of filters. The architecture is further improved by adding a dropout layers are also used to avoid overfitting. When tested on photos from the Kaggle Dataset, the suggested technique gets excellent classification results.

KEY WORDS

VGG-16, Brain Tumor, Convolutional Neural Network (CNN).

INTRODUCTION

Background

A brain tumour which is a life-threatening malignancy is caused by uncontrolled and abnormal cell partitioning. Deep learning improvements in the medical imaging area have assisted in the identification of a number of diseases. For visual learning and image identification, the CNN architecture is the most popular and extensively used machine learning approach. In this report, we use a convolutional neural network (CNN) technique [1] combined with Data Augmentation and Image Processing to analyses MRI images to determine which images have and which do not have brain tumors.

Tumor detection using MRI data is a critical, yet time-consuming, and challenging task that is often done by hand by medical experts. Medical image segmentation takes a long time for radiologists and other medical experts. However, precisely identifying a brain tumor takes a long time, and there is a lot of difference among doctors.

To overcome these constraints, computer-assisted technology is critical, as the medical field requires quick and reliable procedures to identify life-threatening diseases such as cancer, which is the top cause of death for patients worldwide. Hence, utilizing Brain MRI Images, we present a method for classifying MRI images into those with and without the presence of a brain tumors utilizing a data augmentation strategy and a convolutional neural network model in our study.

Motivation

The effects of a brain tumor are long-term, and not only physical but psychological also. A brain tumor is caused by a tissue anomaly that develops inside the brain or central spine, interfering with normal brain function. A primary brain tumor affects around 700,000 people in the most developed countries today, with another 85,000 expected to be diagnosed in 2021. Tumors of the brain can be life-threatening. Brain tumors can be fatal, have a severe impact on quality of life, and completely transform a patient's and their family's lives. They afflict men, women, and children of all races and nationalities without discrimination. Additionally, manual analysis of MRI images and the risk of inaccurate result make the situation even graver. Therefore, all these above factors motivate us to design an algorithm to effectively and accurately predict presence of brain tumor and contribute towards society

Contribution

In this work we have used Convolutional Neural Network to segment MRI images into two categories, those that have tumor and those that do not. The dataset consists of 253 images, with 155 with tumor and 98 without tumor. Once the model is prepared, individual MRI images can be segmented by taking as input. The major contributions are listed below:

- Convolutional neural networks work by accessing information extracted from images to perform tasks like tumor segmentation.
- The network is first trained using a manually segmented dataset before being used to segment patient images.
- Segmented pictures can be used to predict clinical outcomes such as survival and treatment response

Literature Survey

The neoplasm in the brain tumor can be at varying locations and shapes, and during the time of segmentation atlas can be calculated [2, 3]. The voxel neighborhood provides information to the Markov Random Fields, allowing for smoother segmentation results (MRF). Brain tumors are segmented using the MRF approach. Generative models successfully generalize hidden data with some constraints in the training step. Without the use of a specific model, these strategies can be utilized to comprehend the pattern of a brain tumor. The distribution of identical and independent voxels based on context factors is frequently taken into account in these methods.

As a result, some small or isolated clusters of voxels may be categorized mistakenly into the wrong class, typically in anatomically and physiologically incongruent places. To avoid these issues, many researchers used probabilistic predictions to insert neighborhood information into a Conditional Random Field (CRF) classifier. Deep CNN models [4, 5] are used to automatically learn hierarchies of complex data attributes

In this work we have implemented pre-trained and a improved version of VGG-16 Convolutional Neural Network (CNN) to categories brain tumor images taken with camera into two categories namely cancerous and normal images.

VGG-16

VGG16 is a widely used Convolutional Neural Network (CNN) Architecture that was developed for ImageNet, a large visual database project used in the development of visual object recognition software. Karen Simonyan and Andrew Zisserman of the University of Oxford developed and introduced the VGG16 Architecture in their article “Very Deep Convolutional Networks for Large-Scale Image Recognition” published in 2014. The abbreviation ‘VGG’ stands for Visual Geometry Group, a group of researchers at the University of Oxford who developed this architecture, and ‘16’ indicates that there are 16 layers in this architecture (explained later).

In ImageNet, a dataset with over 14 million images divided into 1000 classes, the VGG16 model scored 92.7 percent top-5 test accuracy. It was one of the well-known models that had been submitted.

Proposed System

We propose a technique that is sequential in its operation. It uses techniques such as convolutional neural network, max pooling, flattening and a dropout layer to avoid over-fitting. We use transfer learning to assign weights to our features. The MRI image sequentially goes through the above stated layers and feature extraction is performed. Fig. 1 depicts the basic block diagram of the proposed automatic brain tumor detection system. In Fig. 1, we can see that the MRI images have been divided into two parts where the first part is used for further training of a modified pre-trained VGG-16 CNN. Subsequently, the rest part of images have been used to validated and test the performance of the proposed system. Later, Algorithm 1 demonstrates the step-by-step working process of the proposed system.

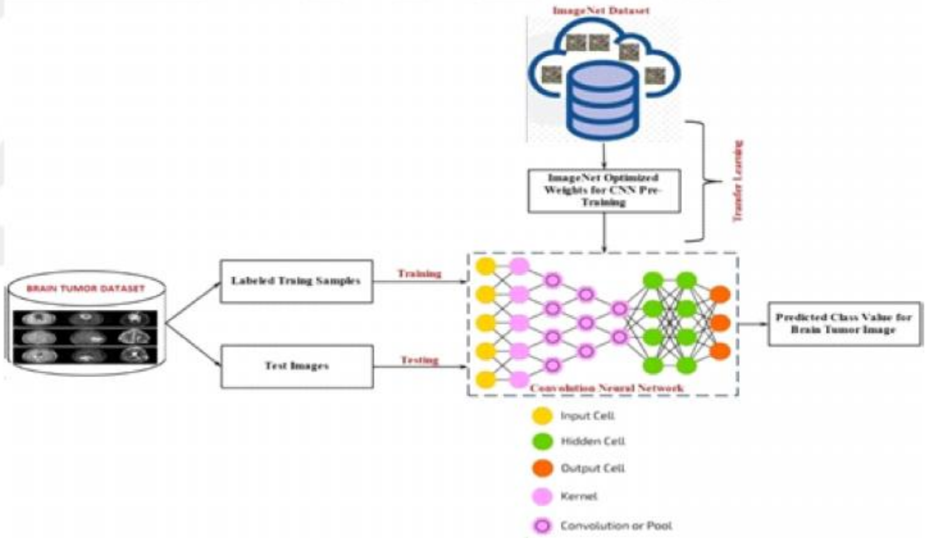


Fig. 1: *Basic block diagram of the proposed automatic brain tumor detection system.*

Input: Input a Brain Tumor query image I_q.
Output: Identified Class C_q of the image I_q.
Parameter: I_q must be a Brain Tumor MRI image.

Select the Brain Tumor Data-set Z_n, where $n = |Z|$.
Split the Data-set Z_n in two parts as Z_{nT} and Z_{nV}.
Assign 80% image of Z_n to Z_{nT} for training of CNN.
Assign class label information to every image of Z_{nT} for training of CNN.
Assign 20% image of Z_n to Z_{nV} for testing and validation of CNN.
Initialize the network weights with the ImageNet optimized weights to perform transfer learning.
for $\forall I_i \in Z_{nT}$ **do**
    Perform supervised trainining of the CNN
Select the input query image $I_q \in Z_{nV}$.
Resize the I_q to **244 x 244** pixels.
Feed the I_q to the trained CNN architecture for class prediction.
Display the predicted class value C_q as final output.

Further, Fig. 2 demonstrates the detailed working model of the proposed brain tumor detection system.

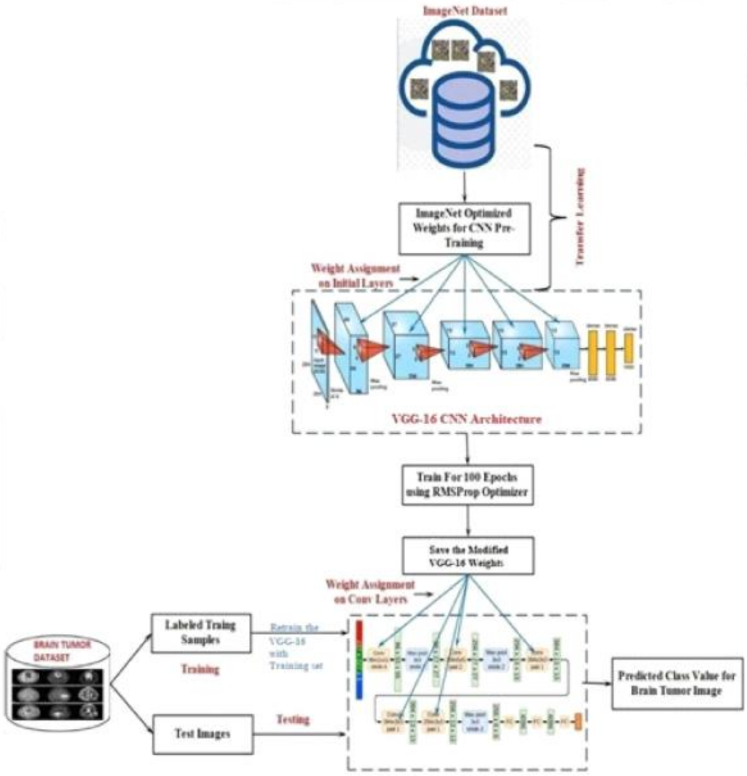


Fig. 2: *Detailed working model of the proposed brain tumor detection system.*

Experimental Results and Discussion

Dataset Description

The dataset used in the project is Brain MRI Images for Brain Tumor Detection by N. Chakrabarty, which is publicly available on Kaggle. The dataset includes 253 images of brain MRI images, out of which 155 contain tumour and 98 images do not contain tumour. Our dataset was divided into three sections for training, validation, and testing. The training data is used to learn the model, while the validation data is used to evaluate the model and adjust its parameters. The training data consists of 80% of the data and rest 80% is for testing. The validation is performed using Cross-Validation. Our model's final evaluation will be based on the test data.

Results and Outcomes

To test the performance of the proposed algorithm we have tested it on 243 MRI images, out of which 155 images have tumor related issues and 98 do not have tumor. Out of those images we selected 20 images for testing. The findings of our suggested image segmentation methodology, which were achieved using real brain MR data, are presented in this section. Jupyter Notebook was used to test the suggested approach.

First the images were reshaped into 244×244 size and passed through a convolutional layer with three filters. Subsequently, the output passes through maxpool and flattening layers. The model has been trained with 30 epochs. Our model has shown an average accuracy of 92.34%. The model loss curve and accuracy curve for training and testing has been shown on Fig. 3 and Fig. 4 for 30 epochs. Further, Fig. 5 shows some sample output of the proposed system for different query images.

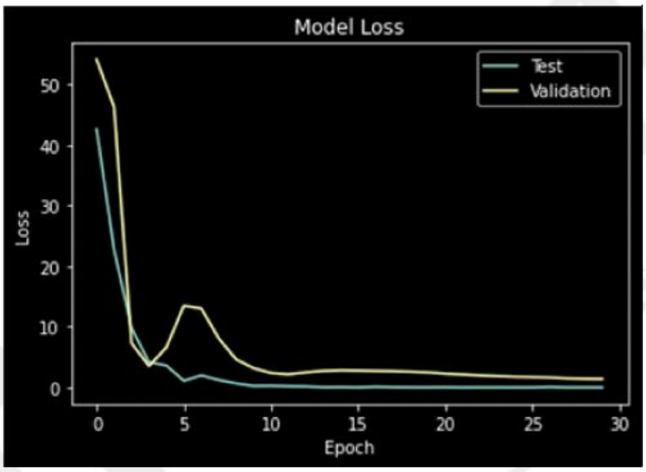


Fig. 3: *The testing and validation loss curve for 30epoches.*

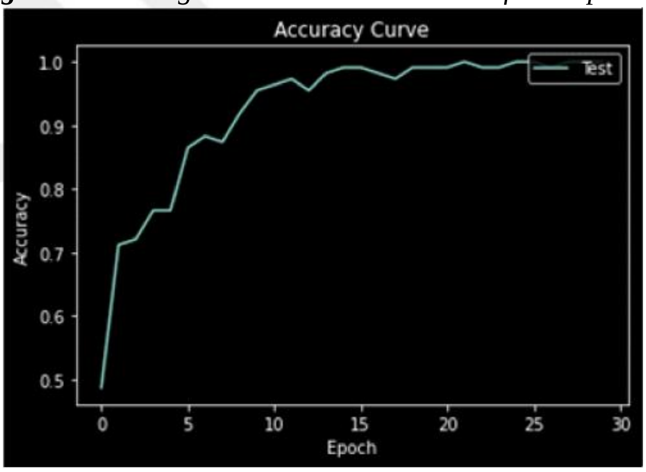


Fig. 4: *The testing accuracy curve for 30epoches.*

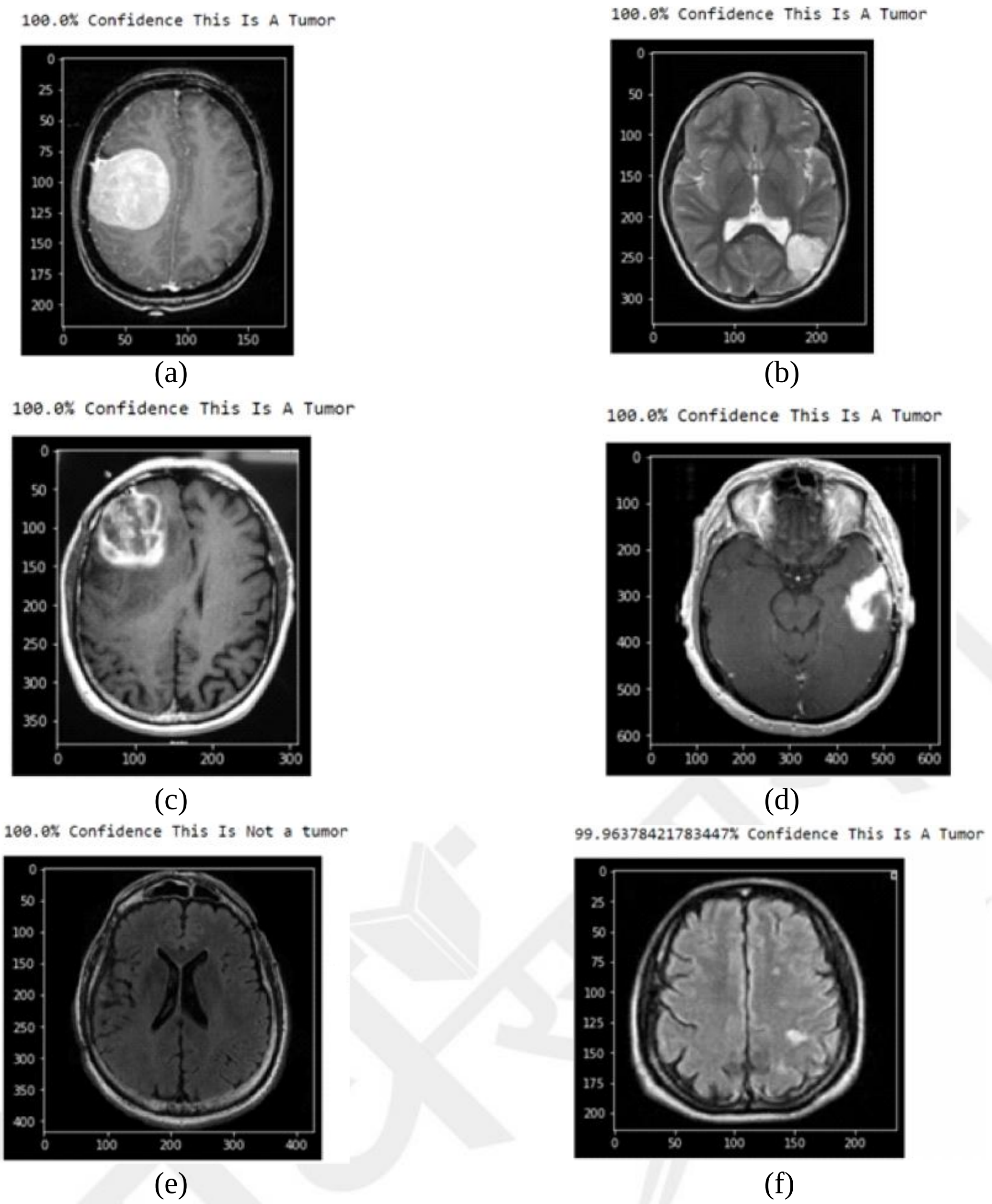


***Fig. 5:** Some sample output achieved from the proposed system.*

CONCLUSION AND FUTURE SCOPE

Conclusion

In this project, we used MRI images of the brain to segment into two sections, having brain tumor or those that do not have tumor. We implemented a sequential model where the MRI images are reshaped to 244 x 244 then they go through the convolutional layer, max-pooling layer, flattening is performed on those images to convert it to a vector form. Furthermore, we used ImageNet dataset which contains a large number of medical images, which helps in feature optimization. The broad architecture used is VGG-16 which is further improved by using a dropout layer. When compared to manual detection done by radiologists or clinical experts, the results of the experiments on various images show that the analysis for brain tumour detection is fast and accurate. Our findings suggest that the proposed method can aid in the accurate and early detection of brain tumours, as well as the pinpointing of their specific location. As a result, the proposed method is important for detecting brain tumours from MR images.

The experimental results were 92.34% percent accurate, indicating the suggested technique's efficacy in distinguishing normal and pathological tissues from MR images. According to our findings, the proposed strategy is appropriate for integrating clinical decision support systems for primary screening and diagnosis by radiologists or clinical experts.

Future Scope

Our proposed system is for binary classification problems. The suggested approach can, however, be expanded for categorical classification issues in future research. These issues can be proper diagnosis of Glioma, Meningioma, and Pituitary tumors, as well as other brain disorders. Adjusting the design such that it can be utilized during brain surgery for identifying and precisely locating the tumour will be one of the most significant advances. Detecting tumours in the operating room should be done in real time and under realistic circumstances. As a result, by adapting the network to a 3D system while keeping the network architecture basic, detection in real time may be achievable. We'll test the performance of our built neural network, as well as enhanced versions, on more medical images in the future.

REFERENCES

1. Mohsen, Heba, El-Sayed A. El-Dahshan, El-Sayed M. El-Horbaty, and Abdel-Badeeh M. Salem, Classification using deep learning neural networks for brain tumors, Future Computing and Informatics Journal, 3 (1), 68-71 (2018).
2. Chavan, Nikita V., B. D. Jadhav, and P. M. Patil, Detection and classification of brain tumors, International Journal of Computer Applications, 112(8), (2015).
3. Banan, Rouzbeh, and Christian Hartmann, The new WHO 2016 classification of brain tumors—what neurosurgeons need to know, Actaneurochirurgica, 159(3), 403-418 (2017).
4. Mohsen, Heba, El-Sayed A. El-Dahshan, El-Sayed M. El-Horbaty, and Abdel-Badeeh M. Salem, Classification using deep learning neural networks for brain tumors." Future Computing and Informatics Journal 3, no. 1 (2018): 68-71.
5. Mehrotra, Rajat, M. A. Ansari, Rajeev Agrawal, and R. S. Anand, A Transfer Learning approach for AI-based classification of brain tumors, Machine Learning with Applications 2, 100003 (2020).

****