Brain Tumor Detection Using Cnn

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Abstract: Artificial Intelligence has greatly benefited the medical field. One of its many diverse applications includes the use of AI in diagnosis to minimize the error due to human judgment. There are a variety of imaging techniques that are being used in recent times that include Computed Tomography Scan (CT), Magnetic Resonance Imaging (MRI), etc., MRI is one the most reliable techniques owing to its reliability and safety. This paper aims to present a similar technique wherein we propose to use a convolutional neural network to detect the presence of the tumor.

Keywords: CNN, Deep Learning, Segmentation, and Computer Vision, VGG-16

1. Introduction

The brain is one of the most important in the human body. It enables humans to interpret information and respond to external stimuli. The basic structure of the brain. There are three main structural units to the brain are Cerebrum, Cerebellum Brainstem (Medulla).The cerebrum is the largest part of the brain, composed of left and right hemispheres.The cerebrum is responsible for, interpreting touch, vision, and vision, speech, reasoning, emotions, movement, and learning.The cerebellum is responsible for muscle movement, posture, and balance.The brainstem connects the cerebellum and cerebrum to the spinal cord. The functions of the brainstem include breathing, heart rate, body temperature, wake and sleep cycles, digestion, and other involuntary activities.

The hemispheres of the Brain can further be divided into Lobes. Each hemisphere has four lobes namely:

1. Frontal
2. Temporal
3. Parietal
4. Occipital

The lobes are functional components of the brain, their function is listed below:

Table 1. Lobes and Fuctionaity

Lobes	Functionality
Frontal Lobe	Problem Solving, Judgment and motor function, Speech, Intelligence, concentration
Parietal Lobe	Sensation, Handwriting and Body Position, Spatial and Visual information
Temporal Lobe	Memory and Hearing Language Interpretation and Understanding
Occipital Lobe	Visual (Color, light, movement)

Neuroanatomy is the study of the anatomy of the brain, neuroscience is the study of understanding its functionality. Medical Imaging technologies have greatly helped scientists study the anatomy and functionality of the brain.

A brain tumor is an abnormal mass of tissue in which cells multiply uncontrollably also known as an intracranial tumor. There are about 150 different types of brain tumors. However, they are broadly categorized into two categories namely primary and metastatic.

Primary tumors that originate from the tissues of the brain or the brain's immediate surrounding. Primary tumors are further categorized based on composition i.e., glial or non-glial. They are also categorized under the category of benign or malignant.

Metastatic tumors originate elsewhere in the body and migrate to the brain via the bloodstream. These tumors are cancerous and considered malignant.

Benign Tumors are slow-growing tumors that usually occur in one place. Once they are surgically removed, they don't return. These tumors are categorized based on their location in the brain.

E.g., Gliomas are tumors formed in the glial tissues which are responsible for supporting nerve cells and fibers. Meningiomas are formed in the membranes that envelop the brain. Craniopharyngiomas are tumors that grow near the pituitary gland, commonly occurs in children and young adults. Haemangioblastomas occur in the cells lining blood vessels near the brain, spinal cord, and medulla. Pituitary Adenomas are the tumors of the pituitary gland. Acoustic neuromas occur in the nerves that control balance and hearing. Other examples may include Chordomas, Gangliocytomas, Glomus jugulare, Meningiomas, Pineocytomas, Schwannomas

A malignant Brain Tumor is cancerous and leads to a condition known as Brain Cancer. It is different from a benign tumor as it is cancerous and fast-spreading, if undiagnosed it can severely affect other parts of the brain and can sometimes cause serious damage to the spinal cord. E.g.: Astrocytoma occurs in the cells that are thought to provide a framework to the brain, Oligodendroglioma occurs in cells that produce fatty covering for the nerve cell,Ependymoma occurs in cells lining the brain cavities. Other e.g., include Glioblastoma multiforme (GBM), Medulloblastomas**.**

Another way in which brain tumors are categorized is based on how fast they grow and the likeliness of their return once they are fully treated. In this categorization, they are labeled between 1 to 4. A malignant tumor is graded 3 or 4 whereas benign tumors are 1 or 2. Malignant Tumors usually occur in other parts of the body and make their way to the brain via the bloodstream whereas primary tumors occur in the brain initially.

It is important to talk about the anatomy of the brain This is because the severity is decided based on the position and size of the tumor. The position of the tumor helps determine the part of the nervous system that would be most affected. This further decides the method of diagnosis that would be employed for the patient.

In the early days, it was very difficult to identify the presence of a tumor let alone the diagnosis. Tumors were identified according to the cell type and by observing the cells which were obtained during biopsy under the microscope.

With the development of biomedical techniques, this process has become faster and more efficient in recent days. Image Processing techniques can further help doctors identify whether the tumor is primary or secondary, cancerous or non-cancerous, and determine the chances of survival of the said patient. The process of identification and diagnosis of a brain tumor begins with magnetic resonance imaging or by conducting an MRI. All the patients that are suspected to have brain tumors have to undergo MRI scans with 48 hours.

The report of these scans is assessed by special neurologists, this process can be time- consuming and the accurate diagnosis depends on the experience of the neurologists.

The undertaking presents the MRI brain diagnosis support framework for structure segmentation and its analysis using various AI Techniques. The strategy is proposed to portion normal tissues such as White Matter, Gray Matter, Cerebrospinal Fluid, and abnormal tissue like tumor part from MR images automatically.

Brain Tumor Identification is a difficult cycle inferable from the unpredictability of the brain. The identification of tumors mainly relies upon the experience of the Radiologist and Neurologist. The overall cycle from discovery to the diagnosis of brain tumors is tedious.

CNN's have proved to be useful in image analysis and have exceeded the expectation of experts. CNN comes under the umbrella term of deep learning neural network

The main goal of medical image preparation is to recognize accurate and meaningful information using images with the minimum blunder conceivable.

2. Background study

With the development of science and technology, new methods have been employed to increase the efficiency of the models. Multiple techniques have been introduced that mainly use MRI scans to accurately predict the presence of a tumor.

There are multiple models built over the years using various techniques to predict the presence of tumors. These techniques have been elaborated as follows:

Umit Ilhan et. al. [5] suggested a model detect abnormalities in MRIs using the threshold technique. The database used in this model was obtained from The Cancer Imaging Archive (TCIA). The proposed approach generated a model with an accuracy of 94.28% in detecting images with a tumor and 100% accuracy and detecting images without any tumor. This model however not an automatic model and did not work effectively with images with poor contrast. The threshold technique aims to minimize the background technique b using a feedback loop to optimize the threshold value before converting the original greyscale image to binary. The overall success rate for the model was 96%.

B. Devkota et al [3] proposed a model utilizing Mathematical morphological Reconstruction to predict the presence of the tumor. MRI scans were pre-processed using a median filter, Spatial Fuzzy C-means were used for the segmentation process, feature reduction was performed on the segmented image using Principal Component Analysis, classification of images was performed by Support Vector Machine (SVM) with a nonlinear kernel. Due to the high computation cost of the above-mentioned segmentation process, another method using mathematical morphology was also suggested.

This model provided better accuracy than all other models using the same approach however it was not tested in a practical setting.

Zhenyu Tang et al [12] proposed a model based on Multi-Atlas Segmentation (MAS) for detecting the presence of tumor in an MRI Scan. This model used a low-rank filter to obtain a recovered image of the normal brain from an MRI scan containing the tumor utilizing information of normal brain atlases. To further improve the results of the low-rank method which usually produces recovered images with distortion spatial constraints were used, this method has been termed as SCOLOR (Spatially Constrained Low Rank) method the model has shown commendable results when applied on synthetic as well as real MRI Scans. The drawbacks as mentioned by the authors are that the tumor regions should have a distinct appearance when compared to normal brain MRI, also the mass of the tumor might significantly affect the results

Nilesh Bahadure et al [1] suggested a detection model based on Berkeley Wavelet Transformation and SVM to detect the presence of brain tumors. This method of feature extraction involved BWT and SVM. Morphological techniques were used to extract the boundary areas of the images. Post boundary extraction, feature extraction was performed to extract information about the image including color, contrast, etc. The model was capable of producing an accurate result in lesser time compared to other models. The overall accuracy for the model was 96.51% with 94.2% specificity and 97.72% sensitivity.

Aleksandr G. Zotin et. al. [7] introduced via this model a new technique to detect the presence of Brain Tumor.This model implemented FCM or Fuzzy C-means clustering.FCM is a type of clustering in which a data point can belong to more than one cluster. Data points are assigned such that the points in a single cluster are as similar as possible, compared to data points in other clusters. FCM clustering is similar to k means clustering. This method was initially developed by J.C. Dunn and enhanced by J.C. Bezdek. The model using this approach was efficient in detecting the presence of a tumor in MRI. The model worked well even low-resolution images. The input images were passed through a median filter and a Balance contrast enhancement technique was used to further enhance the image characteristics.

The image was then segmented using FCM and edge detection was performed.Olfa Mohamed Limam et. al [6] had proposed a model based on Multi-objective Fuzzy clustering. Clustering algorithms are unsupervised algorithms that segregate various data points based on certain characteristics such that all the data points in a single cluster are as similar as possible compared to data points in other clusters. The multi-objective Fuzzy clustering approach aims to increase the overall efficiency of the model and reduce the time required to segregate the data points into clusters and makes sure that the data points in a single cluster are very similar.

This model was further extended to detect the presence of other types of tumors.

G. Rajesh Chandra et. al [2] proposed the following technique to detect any abnormalities in a patient's MRI Scan.This algorithm utilized a Genetic Algorithm and Support Vector Machine. The spatial Grey Level dependence method was used for feature extraction. SVM was used along with the Genetic Algorithm which is an adaptive heuristic search algorithm[18]. Genetic Algorithms have been used in multiple disciplines of study such as engineering, business, and social science. Genetic Algorithm is inspired by Charles Darwin's Theory of evolution. This combination produced a highly accurate model with an accuracy of 97%.

Akshata Raut et. al. [4] proposed a model that utilized the Thresholding technique and Morphological Operation to detect the presence of tumors in the scanned images. The images were converted into a grayscale image. The grayscale image generated was then exposed to a median filter to remove noise from the image so that it does not interfere with the detection process leading to an incorrect diagnosis[17]. Thresholding was performed on the now filtered images. Thresholding is performed by selecting a required value of T. Based on this value, it can be termed as global, variable, or dynamic/adaptive thresholding. The morphological operation was applied. It involves two processes namely erosion and dilation. Edge detection was performed using Sobel Operator.

This model was capable of predicting the size of the tumor to determine the stage.

Madhupriya G. et al [16] proposed a deep learning model to detect the presence of a tumor. The cascaded architecture was implemented for the model based on convolutional network architecture. Furthermore, the paper made a comparison between two models i.e., CNN and PNN. A probabilistic Neural Network is based on the concept of probability and uses the same to perform the process of segmentation. PNN is a feed-forward neural network.

3. Methodology

The medical field has greatly benefitted from computer vision and artificial intelligence in recent years. The concept of semantic segmentation has been attributed to most of the success. Semantic segmentation is the process of pixel-wise classification of the concerned image. DNN comes under the umbrella term of Artificial Neural Network, which utilizes the concept of semantic segmentation to extract relevant information from the given dataset/images.

ANN or feed-forward neural network is a group of multiple neurons at each layer. These neural networks are called DNN when more than one hidden layer is present.

Some deep networks that have made a significant contribution to the field of computer vision:

1. AlexNet
2. VGG-16
3. ResNet
4. GoogLeNet

The proposed model utilizes VGG-16 architecture.

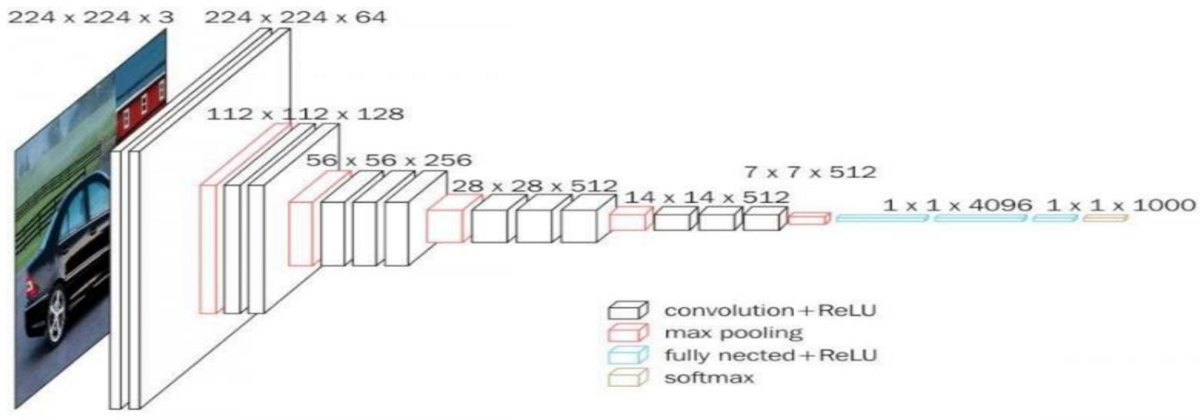

Fig 2. System design for Vgg-16

The Dataset which is used is from Kaggle which consists of a total of 253 images. It consists of MRI scans of two classes:

- NO - no tumor, encoded as 0
- YES - tumor encoded as 1

The NO class consists of 98 images and the YES class consists of 155 images.

Since the dataset is too small and can cause overfitting so the images are pre-processed and data augmentation is applied to get the accuracy. All the imaging datasets have been segmented manually, by one to four raters, following the same annotation protocol, and their annotations were approved by experienced neuro-radiologists.

Annotations comprise the GD-enhancing tumor (ET — label 4), the peritumoral edema (ED— label 2), and the necrotic and non-enhancing tumor core (NCR/NET — label 1), as described both in the BraTS 2012-2013 TMI paper and in the latest BraTS summarizing the paper. The provided data are distributed after their pre-processing, i.e., co-registered to the same anatomical template, interpolated to the same resolution (1 mm^3), and skull-stripped.

4. Experimental Setup

We start with the collection of data for which we use the Kaggle dataset which provides 2 classes of brain images. The two classes are images with a tumor and images without a tumor. We can also use the BraTS dataset which is available in different versions.

For easy understanding, we have divided the dataset into training, validation, and testing data.

Next, we move in towards pre-processing of our data. The first step is to find the biggest contour. The next step is to find the extreme points and then crop the image accordingly. The cropped images are then saved into the respective folders.

The next step is to build the CNN model. For this, we have used Transfer Learning with VGG-16 architecture and weights as a base model. Since the dataset was small, the additional technique of Data Augmentation was used to "increase" the size of the training set. We have set the parameters accordingly which we want to change like rotation, rescaling, brightness, horizontal and vertical flip.

Next, we have built the model using pre-trained VGG16 weights. Then onto these layers, we have added flatten, dropout, and dense layers with Sigmoid activation function and RMSprop optimizer.

The performance of the model is checked by building Accuracy vs Epoch and Loss vs Epoch Graphs. Then we validate the results on the validation and test dataset and check for the misclassified images, therefore seeing the score accuracy.

5. Results

Furthermore, we have plotted two graphs namely:

1. Loss vs. Epoch (Fig.5)
2. Accuracy vs. Epoch (Fig.6)

A confusion matrix for both Test and Validation has been generated.

The Data obtained based on the confusion matrix is as following:

1. Validation Set (Fig.3)
   a. Accuracy: 92%
   b. Sensitivity: 93%
   c. Specificity: 89%

2. Test Set (Fig.4)
   a. Accuracy: 80%
   b. Sensitivity: 80%
   c. Specificity: 80%

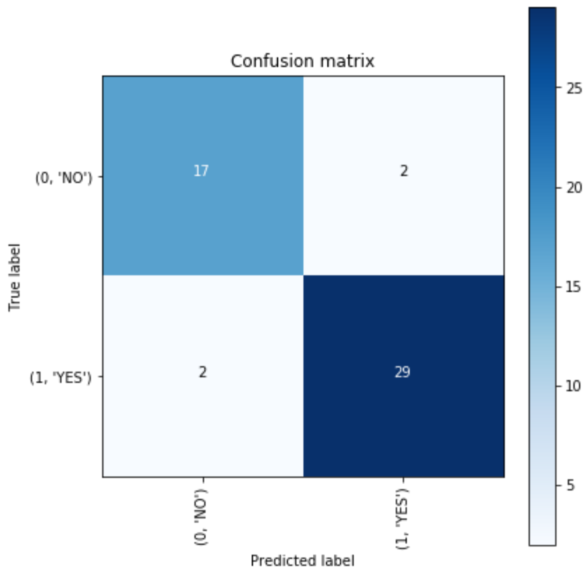

Fig3. Confusion matrix for validation dataset

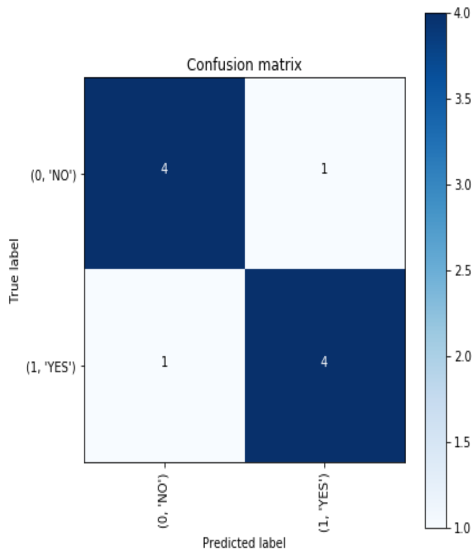

Fig4. Confusion matrix for Test dataset

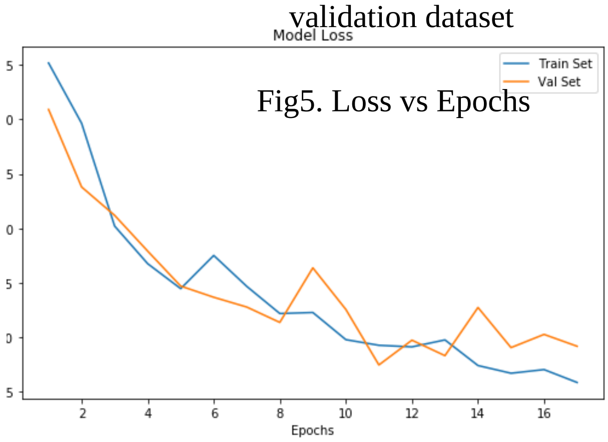

Fig5. Loss vs Epochs

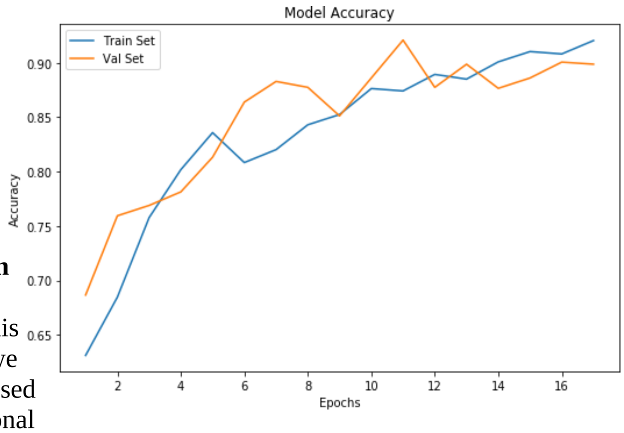

Fig6 Accuracy vs Epochs

6. Conclusion

In this project, we have used Convolutional Neural Network which involves transfer learning using VGG16 to predict whether the MRI image under question contains an abnormal growth in the form of a tumor. The accuracy of our model was calculated to be around 88% for the validation dataset and 90% for the test dataset.

The accuracy of the model can be further improved by using a larger data-set of MRI Scans.

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