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Detection of Brain Tumor using VGG-16 Architecture

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Abstract

Brain tumor is a serious condition caused by abnormal cell development in the brain. It happens as a result of the tissues that surround the brain or the skull. Patients with brain tumors are reported to have trouble walking, speaking, vision problems, vomiting, headaches, seizures, and mental abnormalities. The growth of malignant tissue is detected by magnetic resonance imaging (MRI) images. We introduce a deep learning strategy for detecting the existence of a brain tumor from MRI data that is based on the (Visual Geometry Group) VGG-16 architecture. The dataset comprises of 233 MRI images, including 158 scans with a brain tumor. We achieved an accuracy of 90% on the currently available dataset. The paper focuses on categorizing patients with brain tumors and makes no medical claims about its accuracy.

Keywords: *Brain Tumor; MRI; VGG-16; Deep Learning; CNN*

1. Introduction

Brain tumor refers to the development of cancerous cells in or around the brain. A brain tumor can be benign or malignant. The benign brain tumor has uniform structure and does not contain active (cancer) cells, whereas malignant brain tumors have non-uniform structure and contain active cells. Brain tumors affect people of all ages, and their impact varies from person to person [1]. It has long been one of the main causes of mortality, particularly in developing countries. The American Cancer Society's estimates about 24,530 malignant tumors of the brain or spinal cord will be diagnosed in the United States for 2021 out of which mortality count would be about 18,600 people that include both adults and children [2]. It is tiresome and time consuming for the radiologists and

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doctors in order to treat brain tumor manually. Early detection and diagnosis of the tumor provides patients with additional treatment choices and increases their chances of survival.

Various imaging technologies such as Magnetic resonance imaging (MRI) scan, Computed tomography (CT) scan, Positron emission tomography (PET) scan are used for early detection. An MRI produces detailed images of the brain and monitors the tumor's size. To diagnose a brain tumor, MRIs are more effective than CT scans as they produce more detailed images. However, evaluating the MRI result manually could be tiresome if given the limited time constraint. To overcome this problem, we could analyze the MRI result digitally in order to have accurate and instant diagnosis.

There have been a lot of attempts made in the past for Brain tumor detection using different algorithms and different tools and techniques. Brain tumor is identified implementing ANN (Artificial Neural Network) in the segmented PET images (Positron Emission Tomography) [6]. It used median filter to remove noise from the PET images and implemented Pattern Recognition Technique. Similarly, Kapoor attempted to identify and classify using Gray Level Co-occurrence Matrix (GLCM) based methods and K-nearest neighbor (K -NN) as classifier. The model identifies the tumor in benign stage [7].

We propose a system that implements the machine learning approach to predict the presence of a tumor in the brain or close to the brain based on the MRI images of patients using Convolutional Neural Network. A Convolutional Neural Network, also called as ConvNet or CNN, refers to a Deep Learning algorithm which identifies the input image by assign importance (learnable weights and biases) to various aspects/objects in the image. It requires less preprocessing steps as compared to other classification algorithms. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex [3] .We have implemented VGG-16 architecture of Convolutional Neural Network (CNN) for feature extraction and analysis. This model can assist the medical personnel to identify the tumor and offer the right treatment to the patient at the right time.

2. Materials and Methods

2.1. Dataset

The detection of brain tumor using MRI dataset and overall methodology are explained below .The dataset has been collected from Kaggle/Brain MRI images for brain tumor detection [4]. The collected dataset consists of 233 total MRI Images. The dataset consists of normal and brain tumor images as 98 and 155 files respectively. These MRI Images are preprocessed using data resizing, shuffling, and normalization. The training set and testing set were subdivided through a preprocessed dataset which then implemented on VGG-16 architecture. Different evaluation metrics are employed such as confusion matrix, accuracy, and sensitivity to measure the performance of the system.

2.2. Block Diagram

The block diagram of Brain tumor detection system can be shown in Figure 1. Initially the MRI imag es are collected for analysis .The collected data is then adjusted to extract only the brain part of the im age .MRI's are resized to (224,224) as required by VGG-16 architecture. Data augmentation is performe d to extract different variations of MRI's through shuffling, resizing, rotating, shifting for the purpose of increasing training datasets. The augmented images are taken as input by the VGG-16 model. Under the context of proper learning environments, a VGG model is generated for brain tumor detection. The train ing is followed by testing and validation which analyze the model performance and accuracy. The mode

l provides us with probabilistic output which helps us to detect if the MRI has brain tumor.

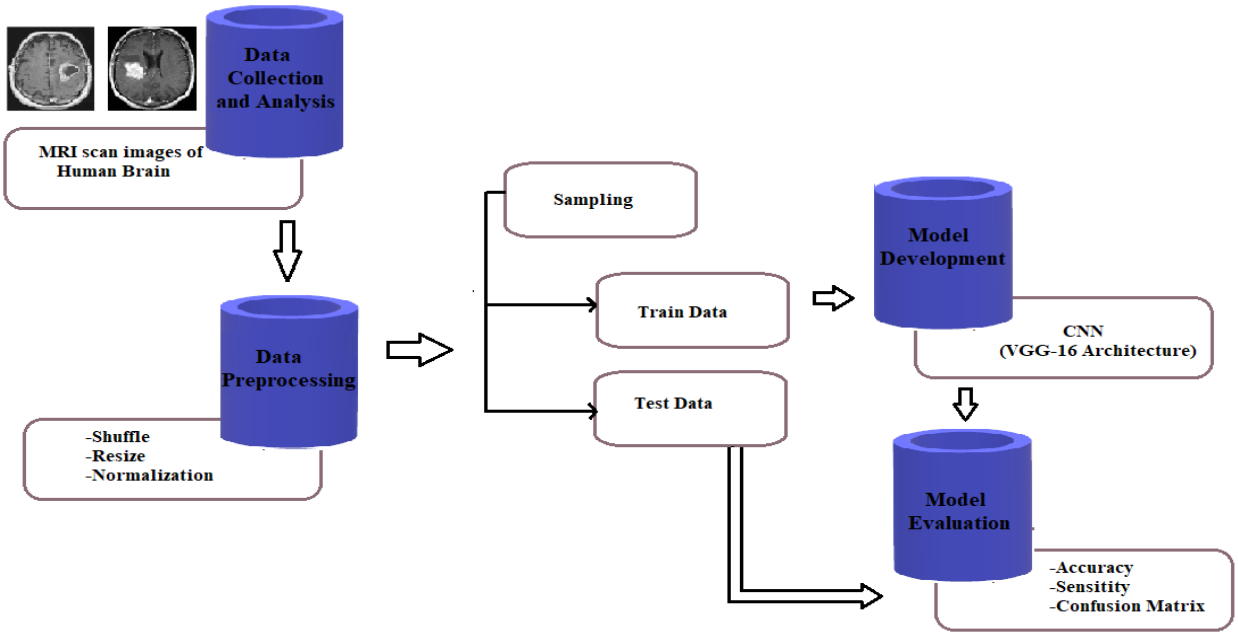


Figure 1. Block Diagram of Brain Tumor Detection System using VGG-16 architecture

2.3. Convolutional Neural Network

In deep learning, a convolutional neural network (CNN or ConvNet) refers to the class of deep neural networks, most ordinarily applied to analyzing visual aspects of an image [5]. VGG-16 is a Neural network based on CNN widely used for image processing. 16 layers of VGG-16 comprise of three layers of CNN, namely, convolutional, pooling, and fully-connected layers.

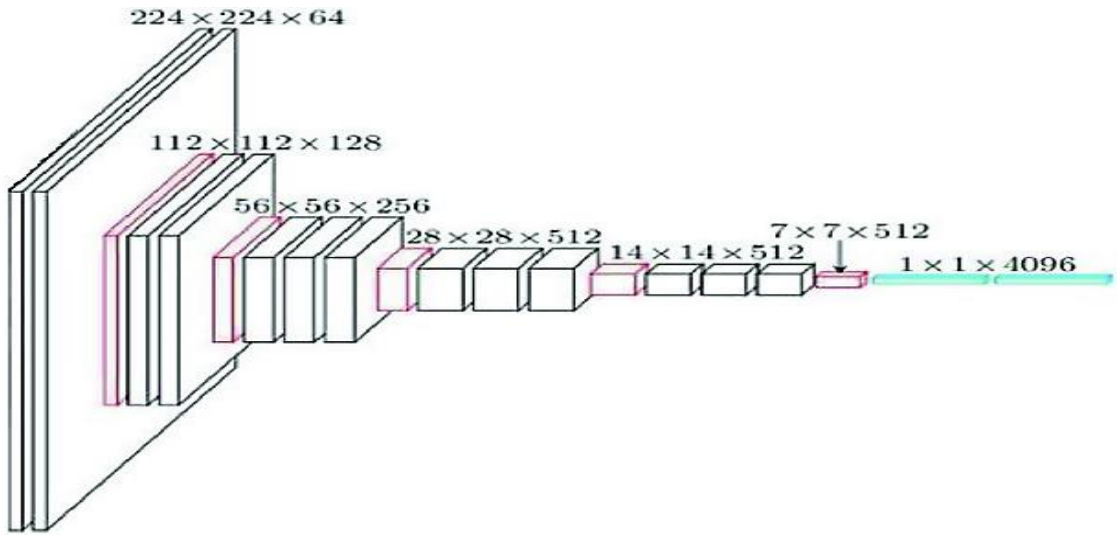


Figure 2. Architecture of VGG-16 Network

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 4096)	102764544
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 2)	8194

Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0

Figure 3. Layers used in VGG-16 architecture for Brain Tumor Detection System

Convolution layer performs the extraction of features from an input image and hence outlines filter or kernel. It learns the image features and uses small squares of input data preserving the connection between pixels named Convolved Feature/Feature Map and has filter size of 3X3. Pooling layers reduce the quantity of parameters when the images are overlarge thus prevents over fitting of input data. Each convolutional layer is followed by pooling layer that reduces the input size by half and feeds it to next batch of convolutional layer as in Figure 2. The output after operation of both convolutional and pooling layers aggregates to high-level features of the input image .The Fully Connected layer acts as a Multi-Layer network that implements activation function in the output layer. The sigmoid activation function provides the probabilistic result that helps us to detect brain tumor.

3. Results and Discussion

Brain Tumor Detection System can be considered as an innovative tool for medical personnel to identify tumors and offer the right treatment to the patient at the right time. In this model, a total of 233 MRI scans were implemented; training 145 x-rays and testing 88 x-rays were taken using 4 convolution layers with 2 dense layers and 10 steps per epoch and 10 epochs to train the data.

The performance of the proposed system can be shown through confusion matrix as shown in Figure 5. As the epoch increases, the loss decreases. Eventually, we should be able to visualize output with training and validation

datasets. The model is found to be predicting occurrence of Brain Tumor with 95.7% accuracy and 1.3% loss. The accuracy can be improved further by increasing the number of dataset. It can be modeled better using significant data, increasing epoch steps and number of epochs, adding checkpoints. The result clearly focuses on identifying tumors in the brain of human body and does not claim any medical accuracy.

```
Epoch 1/100
2/2 [==============================] - 54s 27s/step - loss: 0.9895 - acc: 0.5625 - val_loss: 0.5468 - val_acc: 0.7
500

Epoch 00001: val_acc improved from -inf to 0.75000, saving model to vgg16_1.h5
Epoch 2/100
2/2 [==============================] - 24s 12s/step - loss: 0.8483 - acc: 0.6562 - val_loss: 0.1913 - val_acc: 0.9
062

Epoch 00002: val_acc improved from 0.75000 to 0.90625, saving model to vgg16_1.h5
Epoch 3/100
2/2 [==============================] - 16s 8s/step - loss: 0.3318 - acc: 0.8750 - val_loss: 0.0474 - val_acc: 1.00
00

Epoch 00003: val_acc improved from 0.90625 to 1.00000, saving model to vgg16_1.h5
Epoch 4/100
2/2 [==============================] - 14s 7s/step - loss: 0.2716 - acc: 0.9062 - val_loss: 0.2542 - val_acc: 0.84
38

Epoch 00004: val_acc did not improve from 1.00000
Epoch 5/100
2/2 [==============================] - 11s 6s/step - loss: 0.2479 - acc: 0.9219 - val_loss: 0.2267 - val_acc: 0.90
62

Epoch 00005: val_acc did not improve from 1.00000
Epoch 6/100
2/2 [==============================] - 11s 6s/step - loss: 0.1248 - acc: 0.9531 - val_loss: 0.1960 - val_acc: 0.90
62

Epoch 00006: val_acc did not improve from 1.00000
```

Figure 4. Training for Brain Tumor Detection System using VGG-16 architecture

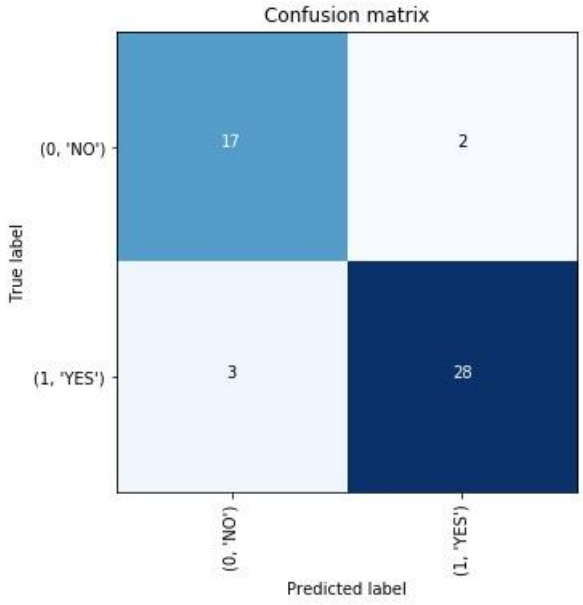


Figure 5. Confusion Matrix for Brain Tumor Detection System using VGG-16 architecture

- TP – 17, MRIs with tumor were correctly identified as MRIs with tumor
- FN – 2, MRIs with tumor were identified MRIs without tumor
- TN – 28, MRIs without tumor were identified as MRIs without tumor
- FP – 3, MRIs without tumor identified as MRIs with tumor

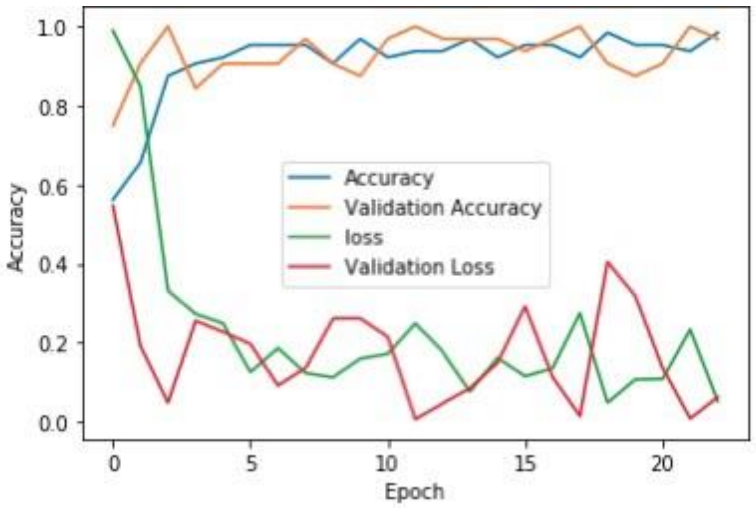


Figure 6. Training and Validation for Brain Tumor Detection System using VGG-16 architecture

Brain Tumor Detection System mainly aims on detecting brain tumor accurately and in speedy manner. It primarily focuses on eliminating the tiresome and time consuming manual task of radiologists and doctors. The Brain Tumor Detection System intakes MRI scanned images of Brain and delivers output specifying if there's tumor in the brain or not. The model provides us with good accuracy. For the further improvement, more dataset can be trained and various other deep learning techniques can be implemented. Moreover, the Brain Tumor Detection System serves as a means to increase the survival rate of brain tumor patient by offering right treatment in right time.

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