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# Brain Tumor Classification using Deep Learning

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***Abstract*—A brain tumour is an abnormal aggregation of cells within the human brain. The skull is incredibly robust and encloses the brain. Any expansion inside such an area might cause issues. Brain tumors can be of two types i.e. cancerous (malignant) or non cancerous (benign). Brain cancer is a fatal disease and it affects all the diagnosed people severely. Accurate classification of brain tumor helps in early diagnosis of brain cancer, which increases the survival rate of brain cancer patients. It is difficult to evaluate the magnetic resonance imaging images manually. Therefore there is a requirement of fast and accurate computerized methods for tumor diagnosis. In this work we are using a deep learning model based on convolutional neural networks to identify and classify brain tumor and its type from MRI images of patients using publicly available dataset in kaggle. In this paper, we are using a VGG16, Convnet and Efficiennet-B0 models for deep learning multi image classification which classifies input image into one of four types like meningioma, glioma, pituitary and no tumor. The dataset includes 5712 and 1311, training MRI and testing MRI images respectively. The models VGG16, Convnet and Efficientnet-B0 achieves 96.27%, 84.13%, 92.5% accuracy respectively, a significant performance with a best overall accuracy of 96.27% provided by VGG16 model.**

***Index Terms*—Deep learning, Brain tumor, CNN, MRI, VGG16, Data augmentation, Efficientnet-B0, ConvNet.**

## I. INTRODUCTION

A brain tumor is a collection of abnormal cells within the brain such that cells multiply uncontrollably and invade neighboring healthy brain tissue. Mainly there are two types of brain tumors, malignant (cancerous) and benign (non-cancerous). Brain tumors that originate inside the brain are called primary brain tumors and cancers that begin in other parts of the body and then spread to the brain are known as secondary (metastatic) brain tumors. The growth rate of brain tumors varies greatly. The growth rate and location of a brain tumor determine how it affects the functioning of the nervous system. Treatment for brain tumors depends on their type, size, and location. The signs and manifestations of brain tumors vary widely, depending on the size, location, and growth rate of the brain tumor. Common symptoms caused by brain tumors include frequent, severe and varied patterns of headaches, unexplained nausea and vomiting, visual and mobility impairment and balance disorders. **[1]** Some of the brain tumors, like glioblastoma multiforme, are categorised as malignant and can grow rapidly. Other types like meningiomas grow slowly and are known as benign. The most common primary brain tumors are known as gliomas and are basically derived from glial (or supporting)tissue. Around one-third of all primary brain tumors and other tumors related to the nervous system originate from glial cells. More than half of all gliomas diagnosed in adults fall into glioblastoma type, which a highly aggressive type of brain tumor. One of the most standard type of grade 4 brain cancer is Glioblastoma. It can be present in any of the brain lobes, but mostly they show up in temporal and fontal brain lobes. Human adults are most commonly affected by glioblastomas. Meningioma is a kind of tumor that grows in the cells which are lining the membrane that surrounds the brain. Meningiomas (also called meningeal tumors)form almost a quarter of all intracranial tumors. Most of these tumors are not dangerous. The option of surgery is mainly used to remove meningiomas. Some of the meningiomas might not require treatment immediately and can go undiscovered for years. Pituitary tumors are masses that form in the major endocrine gland called the pituitary gland, a pea-sized gland that resides right below the brain and above the nasal passages inside the skull. Pituitary tumors are extremely rare; according to the statistics of the American Cancer Society, just a few hundred cases have been recorded in the United States. **[2]** The 5-year survival rate is basically the percentage of the total number of persons who stay alive at least 5 years after the tumor is discovered. In the United States, the 5-year survival rate for people with malignant brain or CNS tumors is nearly 36%, and the 10-year survival rate is about 31%. **[3]** The survival of a brain tumour patient is determined by several factors, including the tumor's location in the brain, its kind, size, or form, the tumor's grade, and the patient's age at the time of diagnosis. Slow-growing (low-grade) tumors are far more likely to recover following therapy than the far more dangerous fast-growing (high-grade) tumors. Surgery of tumors for some parts of the brain becomes quite difficult like tumors near the nerves that control sight, spinal cord, etc, due to the fragile and complicated nature of the human brain. Therefore, for some sensitive areas, surgery is notan option, hence for these areas doctors use other treatment methods like radiotherapy or chemotherapy. **[4]** In most of the cases, magnetic resonance imaging (MRI) is used for the detection and diagnosis of brain tumors (MRI). When a brain tumor is revealed through an MRI scan, the most common technique to diagnose the type of tumor is to examine the results of a biopsy on a sample of tissue.

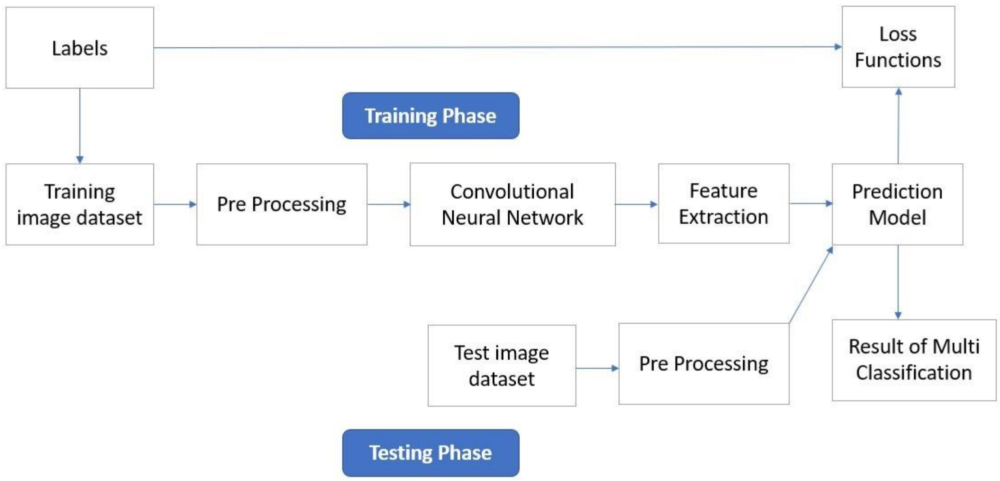


Fig. 1. Block diagram

## II. Related Works

Hossam H. Sultan, Nancy M. Salem, and Walid Al-Atabany **[5]** suggested a DL model, using two publicly available datasets based on a CNN to categorise distinct brain tumor types. The first divides tumors into categories (meningioma, glioma, and pituitary tumor). The other differentiates three forms of glioma (Grade II, Grade III, and Grade IV). For the two studies, the suggested network has the best accuracy of 96.13 % and 98.7 %, respectively.

Chirodip Lodh Choudhury, Brojo Kishore Mishra, Chandrakanta Mahanty, and Raghvendra Kumar **[6]** developed a CNN approach based on deep learning that differentiates between tumor and non-tumor brain MRI images. They have used a three-layer CNN to extract features, followed by a fully connected network with 35 epochs to classify the data. In 35 epochs, the model obtained a training accuracy of 96.08 %.

Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, **[7]**, They used three convolutional neural network architectures (AlexNet, GoogleNet, and VGGNet) are used to classify brain tumors of 3 types like pituitary, glioma and meningioma in their system. Using the fine-tune VGG16 network, they were able to achieve the highest accuracy of 98.69 % of all the studies.

Francisco, Mario, Miriam and David put forward **[8]** a method for brain tumor segmentation and classification based on a CNN (Convolutional Neural Network) architecture built for multiscale processing. They assessed its performance using a dataset of publically accessible T1-weighted contrast-enhanced MRI images. This method obtained the highest tumor classification accuracy with 97.3 %.

Salman Khan, Muhammad Sajjad, Wanqing Wu, Khan Muhammad, Amin Ullah, Sung Wook Baik presented **[9]**, their system in threefold: 1) they have used CNN model to segment tumor regions from the dataset, 2) Then augmentation is used on the segmented data using several parameters which increases the number of dataset samples, and 3) fine tuning of a pre-trained VGG-16 CNN model is done for multi grade brain tumor classification.

## III. Block diagram

Our block diagram of multi classification brain tumor multi classification into four types using deep learning is as shown above. The block diagram is divided into two phases i.e. training and testing phase. We split the dataset into 80% 20% for training and testing respectively. The number of images is divided into different categories by using labels such as Glioma, Meningioma, Pituitary, and No tumor. During the training phase, we conduct preprocessing, augmentation, feature extraction, and classification with Loss function on the input MRI images to make a prediction model. During this phase system load images of training dataset and labels and then makes preprocessing and data augmentation. The CNN models learn features from input data and extract features directly from input MRI images.

The basic properties are learnt when the model trains on a training image dataset, rather than being pre-trained. Deep learning models are particularly accurate for computer vision applications such as tumor classification because of automatic feature extraction. The characteristics are then used to construct a model that categorises the tumors in the image. A deep learning approach is used to automatically extract relevant information from MRI images. Furthermore, deep learning does end-to-end learning, in which a network is given raw data and a goal to complete, such as classification, and it learns how to do so automatically. The main benefit in deep learning networks is that they frequently improve as data amount rises.

In the testing phase, we import the test images and preprocess them before predicting their classes with the learned

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Fig. 2. VGG16 architecture

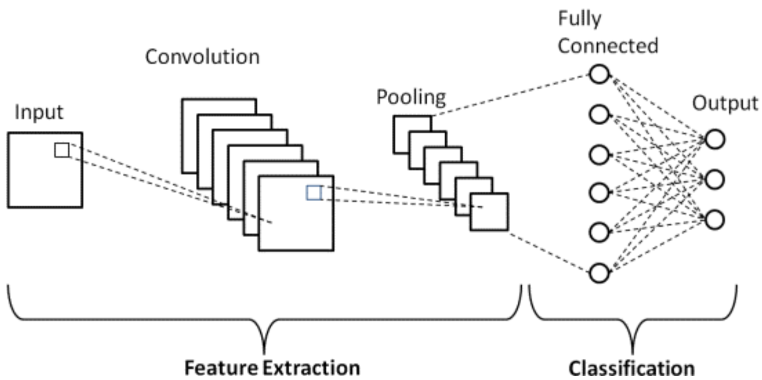


Fig. 3. Basic Convnet architecture

Fig. 4. EfficientNet-B0 architecture

prediction model. The fig 2, fig 3 and fig 4 shows the architectures of models namely VGG16, basic Convnet and EfficientNet-B0.

## IV. METHOD

The methodology that is used to classify brain tumors has the following steps: dataset collection, dataset preprocessing, data augmentation, using CNN models to classify tumors and finally measuring the performance of the system.

Each stage of the proposed system is described below:

### *A. Dataset Collection and Description*

- The brain tumor dataset received from **[10]** includes 7023 MRI images of human brain MRI images which are classified into 4 classes: glioma, meningioma, pituitary and no tumor.
- It has 5712 and 1311 training and testing MRI images respectively.
- Total size of dataset is 160 MB.
- The dimensions of the images in this dataset are different.

### *B. Preprocessing*

A step called preprocessing is done before feeding the data into the explained model. The first stage in this process is to essentially reduce the size of the image, for example from original dimensions into 256x256 pixels so as to reduce dimensionality, computational power and allow the model to give better performance with lower time complexity and more straightforward calculations. The entire data is segregated into two sections i.e. training and testing sets. They all are divided with their own target labels (80% for training and 20% for system testing).

### *C. Data Augmentation*

The augmentation of the images is performed so that the system can know that these images are new ones, and another reason for using it is to minimise overfitting while maximising model robustness. Apart from geometric augmentation, we also use a brightening effect and zoom the input images.

### D. Architecture

- VGG16 Architecture:
  The VGG16 architecture has a total of 16 layers which includes 13 convolutional layers and 3 fully connected layers. The convolutional layers are 3×3 convolutional layers with the same padding and the 2×2 pooling layers. We used ADAM optimizer and Softmax classifier in this CNN model.
  The description of each layer is as follows, firstly the input layer is used to affirm the size of fed images & data normalization is applied so that to transform the input dataset to a uniform size.
  For the next step which is the convolution layer, we extract different features pixel-wise by using feature detectors/kernels. Perform a series of convolutions on the input, each with a different filter which results in the generation of different feature maps. Finally, we combine all of the extracted features to form the final output of the convolution layer.

  The pooling layer is then used, with the goal of continuously lowering dimensionality in order to reduce the number of parameters and computations in the network. This reduces training time and improves control over fitting. Max Pooling extracts the highest pixel value from a feature, whereas average pooling calculates the average pixel value that must be extracted. To achieve spatial invariance, the entire image is split into smaller rectangles (2x2 in the proposed structure) that move over the image with a determined step (2x2) and then accept just the highest value of the four elements. The pooling layer is used to reduce the number of parameters and, as a result, the number of computations in the network.

- EfficientNet (B0) Architecture:
  EfficientNet is a Convolutional Neural Network model that has a scaling method that uses a compound coefficient to scale all depth/width/resolution dimensions. It scales all dimensions like depth/width/resolution with uniformity and a fixed compound coefficient.
  Compound scaling enables EfficientNet models to be scaled in such a way that they achieve state-of-the-art accuracy on ImageNet and other commonly used transfer learning datasets with orders of magnitude fewer parameters and FLOPS **[13]**

- ConvNet Architecture:
  ConvNet is a multi-layer neural network that is specifically designed to recognise visual patterns effectively from images taken with minimal preprocessing. ConvNet architectures usually apply Convolutional Layers to the input in a sequential manner, periodically downsampling the spatial dimensions while lowering the number of feature maps using Pooling Layers. There are four types of layers for a convolutional neural network: the convolutional layer, the pooling layer, the ReLU correction layer, and the fully-connected layer.
  To perform convolution, the kernel iteratively traverses the input image, performing matrix multiplication element by element. The feature map records the result for each receptive field (the area where convolution occurs). We keep sliding the filter until the feature map is finished.

An example of max pooling and average pooling is given in fig 5,

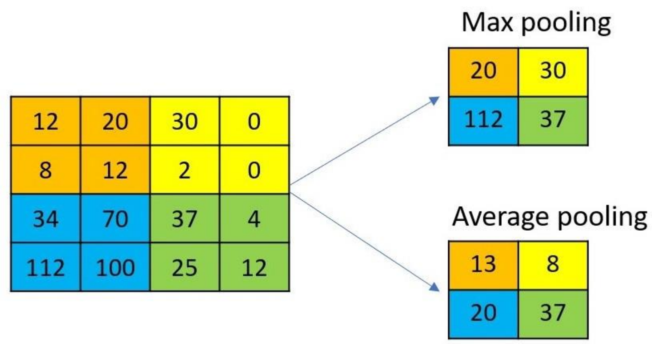


Fig. 5. E.g. of max pooling and average pooling

As for flattening layer, it is basically arranging the pooled feature into a single vector/column as a input for next layer(converting our two dimentional data to one dimentional). An example of the same is as shown in the fig 6.

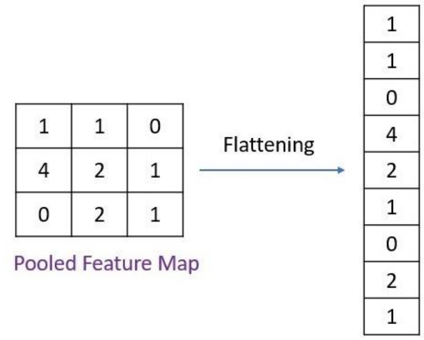


Fig. 6. E.g. of flattening layer

Lastly we use the fully connected layer since neurons in a fully connected layer have full connections to all the activations in the previous layer as shown in fig 7. Higher the number of neurons combined greater will be the predicting accuracy of the model.

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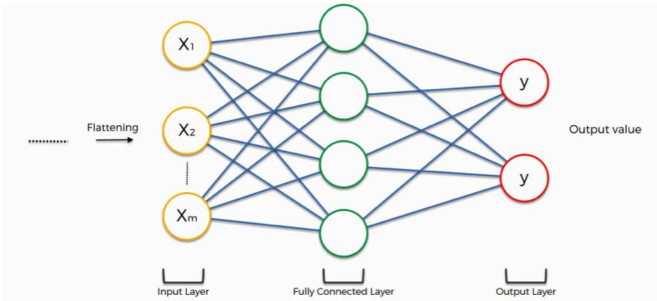


Fig. 7. E.g. of fully connected layer

## V. Experiment and Result

| Training images | Testing images | Algorithm | Accuracy |
|---|---|---|---|
| 5712 | 1311 | ConvNet | 84.13% |
| 5712 | 1311 | Efficient-Net (B0) | 92.50% |
| 5712 | 1311 | Vgg16 | 96.27% |

Table 1. Accuracy comparison of all 3 models

During the testing and validation phase, the various models used in this study as shown in Fig. 8, Fig. 9, Fig. 10, Fig. 11, Fig. 12 displays loss and accuracy. For VGG 16 model testing accuracy is above 96.27%, for convnet as seen in fig. 8 it increases to a maximum of 84.13% and finally for Efficient net model the accuracy obtained is 92.5%. The comparison between the accuracy of the three models can be seen from Table 1.

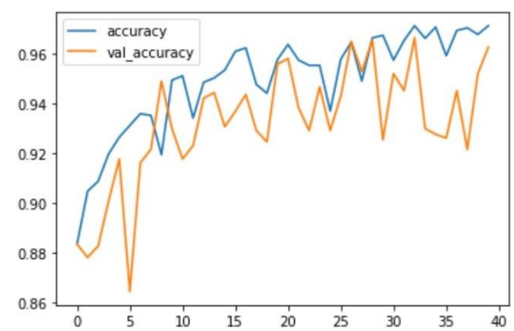


Fig. 8. Training and Validation Accuracy over all epochs for VGG16 model

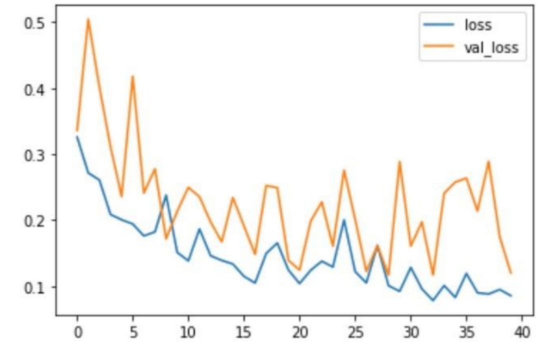


Fig. 9. Training and validation losses over all epochs for VGG16 model

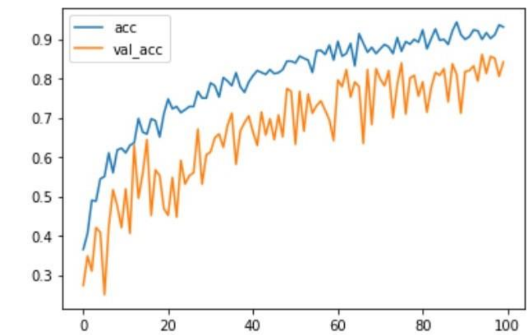


Fig. 10. Training and validation accuracy over all epochs for Convnet model

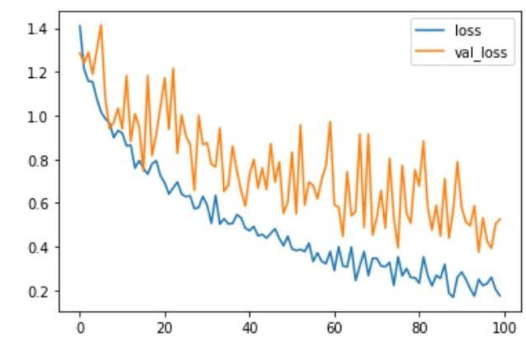


Fig. 11. Training and validation losses over all epochs for Convnet model

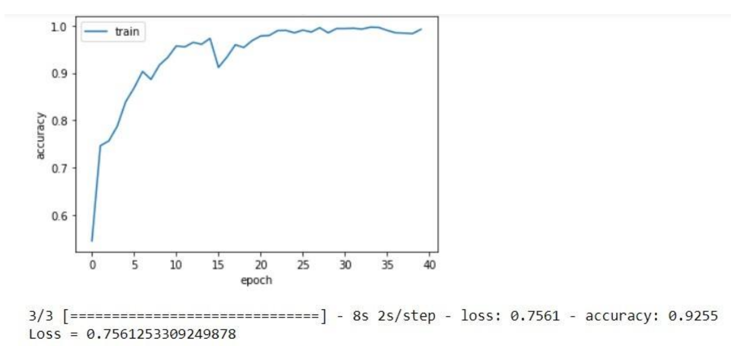


Fig. 12. Training and validation accuracy over all epochs for Efficientnet-B0 model

## VI. Result And Conclusion

In this research, we have introduced a computer-aided approach based on CNN classifying brain tumor MRI images into four categories: meningioma, glioma, pituitary, and no tumor type. We have used three CNN models for this purpose namely the VGG-16 model, the EfficientNet-B0 model, and the modified ConvNet model by increasing the no. of layer by 1 hidden and 1 dropout layer. We have trained these models on the same data set and obtained the accuracy as shown above. We modified the ConvNet model by adding 3 dropout layers, thereby increasing its accuracy from 50.25% to 84.13%. After training VGG16 and EfficientNet-B0 models have achieved the highest accuracy of 96.27% and 92.50% on the validation dataset.

## VII. Acknowledgment

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