

# MRI IMAGE CLASSIFICATION OF BRAIN TUMOUR USING DEEP LEARNING

Vetripriya. M., Kannan, R and T. Sujatha

Dept. of Information Technology, Madha Engineering College, Kundrathur, Chennai-69.

## ABSTRACT

A brain tumour is a mass or growth of abnormal cells in our brain. Many different types of brain tumours exist. Some brain tumours are noncancerous (benign), and some brain tumours are cancerous (malignant). Brain tumours can begin in your brain (primary brain tumours), or cancer can begin in other parts of your body and spread to your brain (secondary, or metastatic, brain tumours). Brain tumour treatment options depend on the type of brain tumour you have, as well as its size and location. The classification of brain tumours is performed by biopsy, which is not usually conducted before definitive brain surgery. The improvement of technology and machine learning can help radiologists in tumour diagnostics without invasive measures. A machine learning algorithm that has achieved substantial results in image classification is the convolutional neural network (CNN). It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully brain tumour normal and abnormal image.

**Keywords:** Brain tumour, neural network, biopsy and surgery.

## INTRODUCTION

Following the classification of the World Health Organization (WHO) astrocytic tumours (gliomas) are divided into four grades, which are typically assigned on the microscopic appearance of the tumour. Grade I comprises pilocytic astrocytoma, and grades II to IV represent invasive tumours having progressive malignancy and worse prognosis. Grade I gliomas are mainly localized respecting anatomic boundaries, whereas grades II to IV gliomas are infiltrating the tissue at different extents (Tandel GS *et al.*, 2019). This characteristic makes an exact localization and an accurate determination of the grade by surgical biopsy difficult. To reach more efficacy non-invasive imaging techniques are used Computed tomography (CT) scanning, magnetic resonance imaging (MRI), positron emission tomography (PET) scanning, and a lot of advanced MR techniques enhance the ability to

localize the tumour and to determine the grading enormously nevertheless in some individual cases there is noticeable disagreement in clinical diagnosis. The reason for this may be mainly attributed to great interobserver variability (Papageorgiou *et al.*, 2008).

## MODULE DESCRIPTION

Module 01: Import the given image from dataset We have to import our data set using keras pre-processing image data generator function also we create size, rescale, range, zoom range, horizontal flip. Then we import our image dataset from folder through the data generator function (Mehrotra *et al.*, 2020). Here we set train, test, and validation also we set target size, batch size and class-mode from this function we have to train using our own created network by adding layers of CNN (Gordillo *et al.*, 2013).

Module 02: To train the dataset by using AlexNet. To train our dataset using classifier and fit generator function also we make training steps per epoch's then total number of epochs, validation data and validation steps using this data we can train our dataset (Khawaldeh *et al.*, 2017).

Module 03: To train the model using LeNetA Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The preprocessing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics (Khan *et al.*, 2020). 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 (Prastawa *et al.*, 2009). Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. Their network consists of four layers with 1,024 input:

Input Layer: Input layer in CNN contain image data. Image data is represented by three dimensional matrixes. It needs to reshape it into a single column. Suppose you have image of dimension  $28 \times 28 = 784$ , it need to convert it into  $784 \times 1$  before feeding into input.

Convo Layer: Convo layer is sometimes called feature extractor layer because features of the image are get extracted within this layer. First of all, a part of image is connected to Convo layer to perform convolution operation as we saw earlier and calculating the dot product

between receptive fields (it is a local region of the input image that has the same size as that of filter) and the filter. Result of the operation is single integer of the output volume. Then the filter over the next receptive field of the same input image by a Stride and do the same operation again. It will repeat the same process again and again until it goes through the whole image. The output will be the input for the next layer.

**Fully Connected Layer:** Fully connected layer involves weights, biases, and neurons. It connects neurons in one layer to neurons in another layer. It is used to classify images between different categories by training.

**Output Layer:** Output layer contains the label which is in the form of one-hot encoded. Now you have a good understanding of CNN.

**Module 04: Deploying the model in Django Framework and predicting output** In this module the trained deep learning model is converted into hierarchical data format file (.h5 file) which is then deployed in our django framework for providing better user interface and predicting the output whether the given image contain tumour or not.

## **SYSTEM REQUIREMENTS**

Hardware requirements:

- Processor - I3
- RAM - 2 GB (min)
- Hard Disk - 80GB

Software requirements:

- Operating system: Windows / Linux
- Software: Anaconda navigator
- Simulation Tool: Pycharm with Jupyter Notebook (Figure 1)

**Functional Requirements:** The software requirements specification is a technical specification of requirements for the software product. It is the first step in the requirements analysis process. It lists requirements of a particular software system. The following details to follow the special libraries like tensorflow, keras, matplotlib.

Non-Functional Requirements: Process of functional steps,

1. Problem define
2. Preparing data
3. Evaluating algorithm
4. Improving results
5. Prediction the result.

### **Algorithm**

Types of CNN:

- Alex Net
- Le Net ALEXNET: AlexNet is the name of a convolutional neural network which has had a large impact on the field of machine learning, specifically in the application of deep learning to machine vision. AlexNet was the first convolutional network which used GPU to boost performance. AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU. The pooling layers are used to perform.

Convolutional Layers: Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.

Dense Or Fully Connected Layers: Fully connected layers are placed before the classification output of a CNN and are used to flatten the results before classification. This is similar to the output layer of an MLP. LENET LeNet was one among the earliest convolutional neural networks which promoted the event of deep learning. After innumerable years of analysis and plenty of compelling iterations, the end result was named LeNet.

Architecture Of Lenet-5: LeNet-5 CNN architecture is made up of 7 layers. The layer composition consists of 3 convolutional layers, 2 subsampling layers and 2 fully connected layers.

**Convolutional Layers:** Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.

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**Drawback and Advantages:**

**Drawbacks:**

- It has not focused on identifying CNN as classifier.
- It has not focused on increasing the recognition rate and classification accuracy of severity of brain tumour.
- Deployment of the model was not implemented.

**Advantages:**

- To identify the Brain tumour disease easily and reduce the workload of doctors in the medical field.
- It is best model for deep learning technique to easily identify the brain tumour.

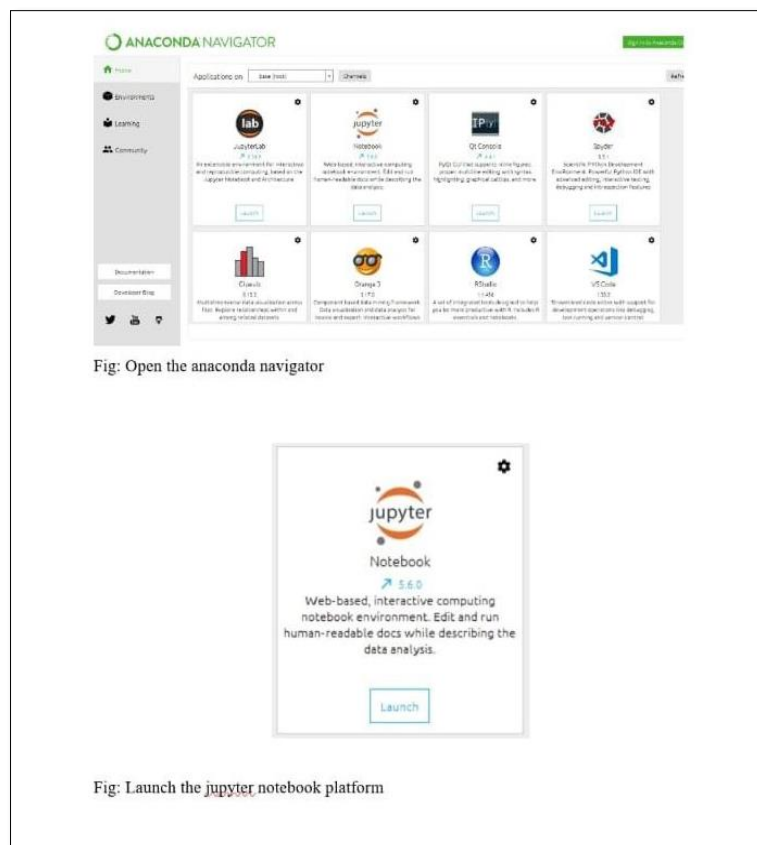


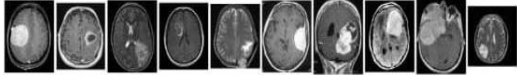
Fig: Open the anaconda navigator

Fig: Launch the jupyter notebook platform

### SCREENSHOTS

Trained data for brain tumor:

```
----- Images in: data/train/yes
image_count: 115
min_width: 176
max_width: 1427
min_height: 219
max_height: 1427
```



Train for 5 steps, validate for 2 steps

Epoch 1/50  
5/5 [-----] - 1s 61ms/step - loss: 17.2111 - accuracy: 0.5676 - val\_loss: 7.7914 - val\_accuracy: 0.4511

Epoch 2/50  
5/5 [-----] - 1s 389ms/step - loss: 4.2199 - accuracy: 0.6814 - val\_loss: 0.7539 - val\_accuracy: 0.7344

Epoch 3/50  
5/5 [-----] - 1s 183ms/step - loss: 1.6857 - accuracy: 0.6149 - val\_loss: 0.5318 - val\_accuracy: 0.7589

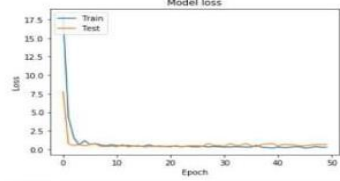
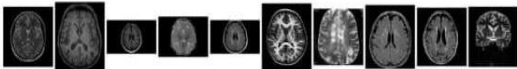
Epoch 4/50  
5/5 [-----] - 1s 388ms/step - loss: 0.6897 - accuracy: 0.7297 - val\_loss: 0.6943 - val\_accuracy: 0.6585

Epoch 5/50  
5/5 [-----] - 1s 416ms/step - loss: 1.1881 - accuracy: 0.6580 - val\_loss: 0.4666 - val\_accuracy: 0.7456

Epoch 6/50  
5/5 [-----] - 1s 480ms/step - loss: 0.6488 - accuracy: 0.7125 - val\_loss: 0.6462 - val\_accuracy: 0.6578

Trained data for no\_tumor:

```
----- Images in: data/train/no
image_count: 65
min_width: 150
max_width: 1024
min_height: 168
max_height: 1024
```



```
-----
| Epoch | Train Loss | Test Loss |
|-----|-----|-----|
| 1     | 17.2111    | 7.7914    |
| 2     | 4.2199     | 0.7539    |
| 3     | 1.6857     | 0.5318    |
| 4     | 0.6897     | 0.6943    |
| 5     | 1.1881     | 0.4666    |
| 6     | 0.6488     | 0.6462    |
| 7     | 0.5676     | 0.7914    |
| 8     | 0.6814     | 0.7539    |
| 9     | 0.6149     | 0.5318    |
| 10    | 0.7297     | 0.6943    |
| 11    | 0.6580     | 0.4666    |
| 12    | 0.7125     | 0.6462    |
| 13    | 0.5676     | 0.7914    |
| 14    | 0.6814     | 0.7539    |
| 15    | 0.6149     | 0.5318    |
| 16    | 0.7297     | 0.6943    |
| 17    | 0.6580     | 0.4666    |
| 18    | 0.7125     | 0.6462    |
| 19    | 0.5676     | 0.7914    |
| 20    | 0.6814     | 0.7539    |
| 21    | 0.6149     | 0.5318    |
| 22    | 0.7297     | 0.6943    |
| 23    | 0.6580     | 0.4666    |
| 24    | 0.7125     | 0.6462    |
| 25    | 0.5676     | 0.7914    |
| 26    | 0.6814     | 0.7539    |
| 27    | 0.6149     | 0.5318    |
| 28    | 0.7297     | 0.6943    |
| 29    | 0.6580     | 0.4666    |
| 30    | 0.7125     | 0.6462    |
| 31    | 0.5676     | 0.7914    |
| 32    | 0.6814     | 0.7539    |
| 33    | 0.6149     | 0.5318    |
| 34    | 0.7297     | 0.6943    |
| 35    | 0.6580     | 0.4666    |
| 36    | 0.7125     | 0.6462    |
| 37    | 0.5676     | 0.7914    |
| 38    | 0.6814     | 0.7539    |
| 39    | 0.6149     | 0.5318    |
| 40    | 0.7297     | 0.6943    |
| 41    | 0.6580     | 0.4666    |
| 42    | 0.7125     | 0.6462    |
| 43    | 0.5676     | 0.7914    |
| 44    | 0.6814     | 0.7539    |
| 45    | 0.6149     | 0.5318    |
| 46    | 0.7297     | 0.6943    |
| 47    | 0.6580     | 0.4666    |
| 48    | 0.7125     | 0.6462    |
| 49    | 0.5676     | 0.7914    |
| 50    | 0.6814     | 0.7539    |
```

```
import matplotlib.pyplot as plt
img = plt.imshow(test_image)
```

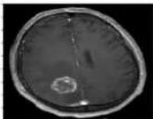


Fig: Open the correspondent result folder

## CONCLUSION

It focused how image from given dataset (trained dataset) in field and past data set used to predict the pattern of brain tumour using CNN model. This brings some of the following insights about tumour prediction. We had applied different type of CNN compared the accuracy and saw that LeNet makes better classification and the .h5 file is taken from there and that is deployed in Django framework for better user interface. Future Work was planned to deployment real time this process by show the prediction result in web application or desktop application and to optimize the work to implement in Artificial Intelligence environment and to deploy this model to AI on web application.

## REFERENCES

- Gordillo, E. Montseny, P. Sobrevilla, State of the art survey on MRI brain tumour segmentation *Magn. Reson. Imaging*, 31 (8) (2013), pp. 1426-1438.
- Khan H A, W. Jue, M. Mushtaq, and M. U. Mushtaq, "Brain tumor classification in MRI image using convolutional neural network," *Mathematical Biosciences and Engineering*, vol. 17, no. 5, pp. 6203–6216, 2020.
- Khawaldeh S, Pervaiz U, Rafiq A, Alkhaldeh RS (2017) Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks. *Appl Sci* 8(1):1–17.
- Mehrotra R, Ansari MA, Agrawal R, Anand RS (2020) A Transfer learning approach for AI-based classification of brain tumors. *Mach Learn Appl* 2(9):1–12.
- Papageorgiou EI, Spyridonos PP, Glotsos DT, Stylios CD, Ravazoula P, Nikiforidis GN, Groumpos PP (2008) Brain tumor characterization using the soft computing technique of fuzzy cognitive maps. *Appl Soft Comput J* 8(1):820–828.
- Prastawa M, E. Bullitt, G. Gerig. Simulation of brain tumours in MR images for evaluation of segmentation efficacy. *Med. Image Anal.*, 13 (2) (2009), pp. 297-311
- Tandel GS, Biswas M, Kakde OG, Tiwari A, Suri HS, Turk M, Laird JR, Asare CK, Ankrah AA, Khanna NN, Madhusudhan BK, Saba L, Suri JS (2019) A review on a deep learning perspective in brain cancer classification. *Cancers* 11(1):1–32.