



Topic:

MRI-Image Classification of brain scans to detect tumor/ no tumor

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Abstract

One of the most deadly diseases in humans is brain tumor. Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. The usual method to detect brain tumor is Magnetic Resonance Imaging(MRI) scans. For brain tumor diagnosis, surgical approaches are usually suggested. But the radiologist's analysis of the medical image is time-consuming and also accuracy totally relies upon their skill. Now, Deep learning-based models have gained considerable interest in the diagnosis and treatment of diseases in medical field. As the medical images are limited, so it is a daunting task to train CNN from start and to implement deep learning. In this project, we develop a model for brain tumor detection based on the pre-trained convolutional neural network architectures such as VGG-19. This pre-trained model is very accurate because it uses multiple 3x3 filters in each convolutional layer. Our model managed to achieve a high accuracy of 96.4%.

Abbreviations

Abbreviations	Full form
DL	Deep learning
CNN	Convolutional neural networks
ReLU	Rectified Linear Unit
PReLU	Parametric Rectified LinearUnit
ELU	Exponential Linear Unit
MRI	Magnetic resonance imaging
VGG	Visual Geometry Group

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1. Introduction

Brain tumor is a mass (i.e. benign or malignant) that is produced by tissue besieging the brain or skull within the brain which impacts a person's life explicitly. These tumors cultivate irregularly in the brain and put pressure around them. Due to this pressure, different brain disorders are induced in the human body. Side effects in patients due to these disorders are dizziness, headache, fainting attacks, paralysis, etc. As stated by WHO, tumor in the brain accounts for less than 2% of human cancers in the cancer report; however, extreme bleakness and problems are registered. The Cancer Research Corporation of UK estimated that almost 5200 casualties are recorded per year in the UK due to brain disorders and skull tumors.

Deep learning (DL) has recently been used mainly in medical imaging. Conventional machine learning involves a great deal of domain expertise, human interaction to retrieve the hand-engineered features, i.e. used by classifiers for classification and detection of image patterns. The specialist manual annotation takes a lot of time.

MRI is a type of medical image modality that is measured by its non-invasiveness as a safe technique and has a reasonable soft-tissue contrast. As attempted by ionizing radiation-based methods, this does not alter the construction, properties, and characteristics of particles. The MRI setting does, however, offer potential hazards due to 3 magnetic fields that are robust static magnetic fields, gradient-based magnetic fields, and pulsed radiofrequency fields that are used to generate 3D images. Eventually, MRI can provide useful information on tissue structures, i.e. shape, size, and location. MRI is being categorized as structural and functional imaging.

Convolutional neural networks (CNNs) are the most useful of many DL techniques that were used to actually solve problems in different applications, including detection, segmentation and classification, etc. CNN layers are input layer, an output layer, and n number of hidden layers. Hidden layers include multi - convolutional layers, pooling layers, fully connected layers, and normalization layers. The computation of the output of neurons that are connected to the input regions is performed by convolutional layers. Each neuron computes the product of its weights. The pooling layer will perform a downsampling operation on the dimensions which are spatial (i.e., width, height). As the name implies, a fully connected layer will have complete connections to all activations in the earlier layer. Different kinds of activation functions are possible to CNN systems such as identity Binary step Logistics (Soft step), TanH, ArcTan, Rectified Linear Unit (ReLU), Parametric Rectified LinearUnit (PReLU), Exponential Linear Unit (ELU), SoftPlus.

2. Problem definition

Our study deals with automated brain tumor detection and classification. Normally the anatomy of the brain is analyzed by MRI scans or CT scans. The aim of the project is tumor identification in brain MR images. The main reason for detection of brain tumors is to provide aid to clinical diagnosis. The aim is to provide an algorithm that guarantees the presence of a tumor by combining several procedures to provide a foolproof method of tumor detection in MR brain images. The methods utilized are filtering, erosion, dilation, threshold, and outlining of the tumor such as edge detection. The focus of this project is MR brain images tumor extraction and its representation in simpler form such that it is understandable by everyone. The objective of this work is to bring some useful information in simpler form in front of the users, especially for the medical staff treating the patient. The aim of this work is to define an algorithm that will result in an extracted image of the tumor from the MR brain image. The resultant image will be able to provide information like size, dimension, and position of the tumor, and its boundary provides us with information related to the tumor that can prove useful for various cases, which will provide a better base for the staff to decide the curing procedure. Finally, we detect whether the given MR brain image has a tumor or not using Convolution Neural Network.

3. Motivation & Objectives

Objective:

- Brain tumor detection and segmentation is one of the most challenging and time-consuming tasks in medical image processing.
- The seriousness of brain tumors is very big among all the variety of cancers, so to save a life immediate detection and proper treatment must be done.
- It is very difficult to have a vision about the abnormal structures of the human brain using simple imaging techniques, thus MRI images are used which provide plentiful information about the human soft tissue, which helps in the diagnosis of brain tumor.

Motivation:

A brain tumor is defined as an abnormal growth of cells within the brain or central spinal canal. Some tumors can be cancerous thus they need to be detected and cured in time. The exact cause of brain tumors is not clear and neither is the exact set of symptoms defined, thus, people may be suffering from it without realizing the danger. Primary brain tumors can be either malignant (contain cancer cells) or benign (do not contain cancer cells). Brain tumors occurred when the cells were dividing and growing abnormally. It is appearing to be a solid mass when diagnosed with diagnostic medical imaging techniques. There are two types of a brain tumor which is primary brain tumor and metastatic brain tumor. The primary brain tumor is the condition when the tumor is formed in the brain and tended to stay there while the metastatic brain tumor is the tumor that is formed elsewhere in the body and spreads through the brain. The symptom having of a brain tumor depends on the location, size, and type of the tumor. It occurs when the tumor compresses the surrounding cells and gives out pressure. Besides, it is also occurring when the tumor blocks the fluid that flows throughout the brain. The common symptoms are having headaches, nausea, vomiting, and having problems balancing and walking. Brain tumors can be detected by diagnostic imaging modalities such as CT scans and MRI. Both of the modalities have advantages in detecting depending on the location type and the purpose of examination needed. In this paper, we prefer to use the MRI images because it is easy to examine and gives out accurate calcification and foreign mass location. The MRI is the most regularly utilized strategy for imaging brain tumors and the identification of their vicinity. The conventional technique for CT and MR image classification and detection of tumor cells remains largely supported for the human reviewing apart from different other methods. MR images are mainly used because there are non-destructive and non-ionizing. MR imaging offers high-definition pictures that are extensively utilized in discovering brain tumors. MRI has diverse schemes such as flair, T1-weighted, T2-weighted images. There are many image processing techniques such as pre-processing, segmentation of images, image improvements, feature extraction, and classifiers.

4. Dataset Description and Data Pre-processing

Dataset Description

The data set consists of two different folders that are Yes or No. Both the folders contain different MRI images of the patients. Yes folder has patients that have brain tumors whereas No folder has MRI images of patients with no brain tumor. There are a total of 155 images of positive patients of brain tumor and 98 images of other patients having no brain tumor. All the images are of 240X240 pixels.

Data Pre-processing:

1. Dataset Augmentation:

As our dataset has 155 images of MRI scans of the brain having a tumor and only 98 of MRI scans of brains not having a tumor, the number of images is less and there is a significant difference in the number of images of MRI scans with tumor and no-tumor. This vast difference can become an issue when we try to train our model and thus will affect its accuracy and efficiency.

To resolve this issue, we augment by taking each image and saving copies of the same image after

rotating or flipping it to create variations. The images in the 'No' folder were augmented more times as compared to the yes folder to create a dataset having balanced data. This will help in training the model efficaciously.

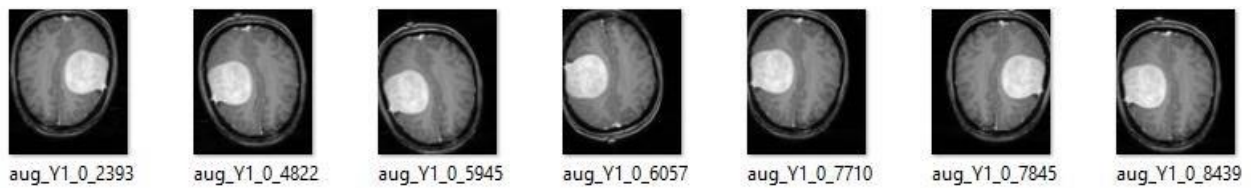


Fig 1: Augmentation of the dataset

2. Image Resize: The size of the images in our dataset were not stable. There were images with irregular shape size which is again a negative point while training our model. To make sizes of all images of the dataset uniform and as the VGG19 model only accepts 224X224 size as input images we converted all the images to this size.
3. Image crop: In order to remove the excess space around the images of MRI scans of the brain, we crop the images. This will improve the accuracy as the model and will not waste time and memory in analyzing the redundant part of the images. We find the extreme points on the image and crop the useful portion out of the image dataset.

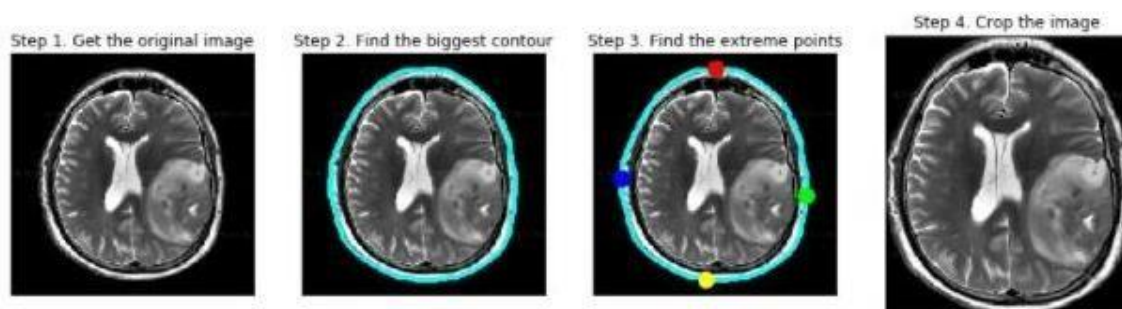


Fig 2: Cropping the images[2]

5. System architecture/Block diagram

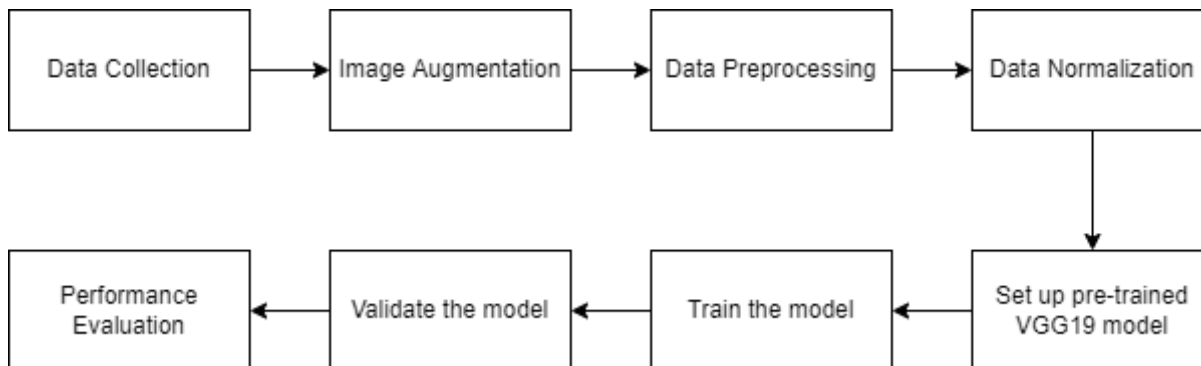


Fig 3: System Architecture

Model architecture:

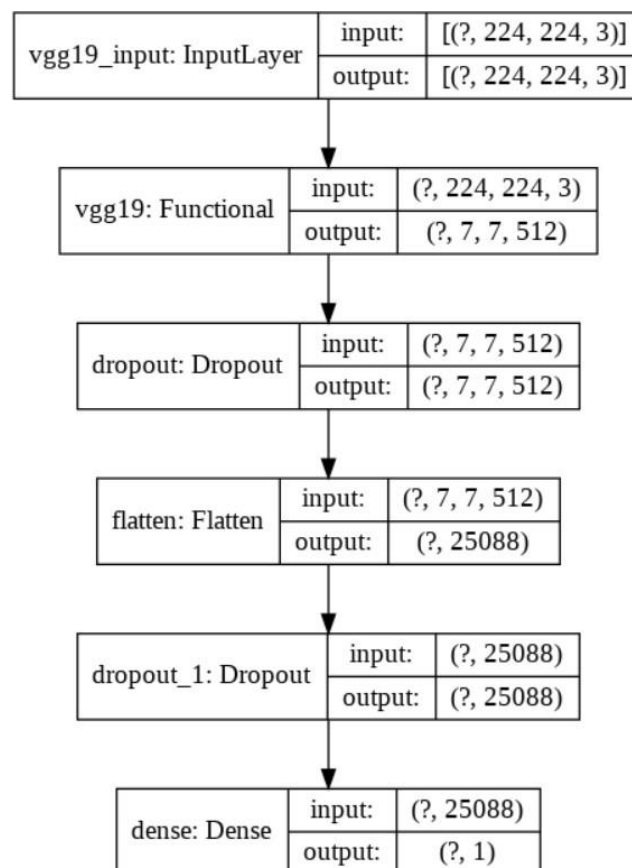


Fig 4: Model Architecture

6. Tasks performed

- Data Collection
- Image Augmentation
- Data Preprocessing
- Data Normalization
- Set up Pre-trained VGG19 model
- Train the model
- Validate the model
- Performance Evaluation

7. Algorithm/Methods/Techniques used:

Library:

Keras:

Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library.

Tensorflow:

TensorFlow is an open-source end-to-end platform for creating Machine Learning applications. It is a symbolic math library that uses dataflow and differentiable programming to perform various tasks focused on training and inference of deep neural networks. It allows developers to create machine learning applications using various tools, libraries, and community resources.

Pandas:

Pandas is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series.

Matplotlib

Matplotlib is an amazing visualization library in Python for 2D plots of arrays. Matplotlib is a multi-platform data visualization library built on NumPy arrays and designed to work with the broader SciPy stack. One of the greatest benefits of visualization is that it allows us visual access to huge amounts of data in easily digestible visuals. Matplotlib consists of several plots like line, bar, scatter, histogram etc.

Numpy

NumPy is a Python library used for working with arrays. It also has functions for working in the domain of linear algebra, fourier transform, and matrices.

Sklearn

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistent interface in Python.

Model :

VGG19:

VGG-19 is a convolutional neural network that is 19 layers deep. You can load a pre trained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

Tools:

Jupyter Notebook

8. Experimentation and Performance metrics

```
# Evaluate the model on test set
score = vgg19.evaluate(X_test, y_test, verbose=0)

# Print test accuracy
print('\n', 'Test accuracy:', score[1])
```

Test accuracy: 0.9641873240470886

Fig 5: Accuracy of VGG19 model

Accuracy: 0.964187
 Precision: 0.977901
 Recall: 0.951613
 F1 score: 0.964578
 Cohens kappa: 0.928380
 ROC AUC: 0.964507
 [[173 4]
 [9 177]]
 Specificity: 0.9774011299435028

	precision	recall	f1-score	support
0	0.95	0.98	0.96	177
1	0.98	0.95	0.96	186
accuracy			0.96	363
macro avg	0.96	0.96	0.96	363
weighted avg	0.96	0.96	0.96	363

Fig 6: Accuracy, Precision, Recall, Support

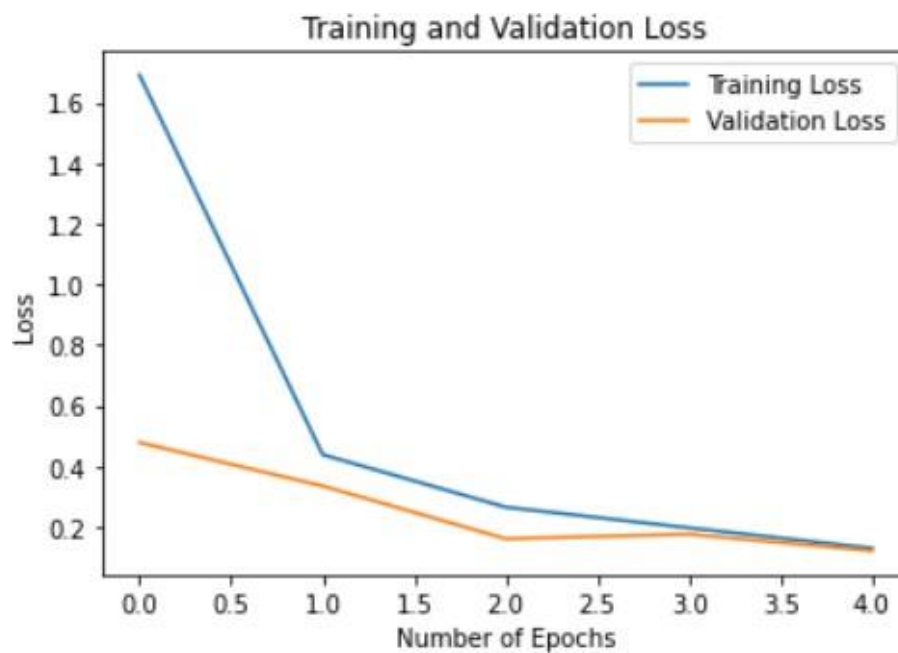


Fig 7: Training and validation loss over 5 epochs

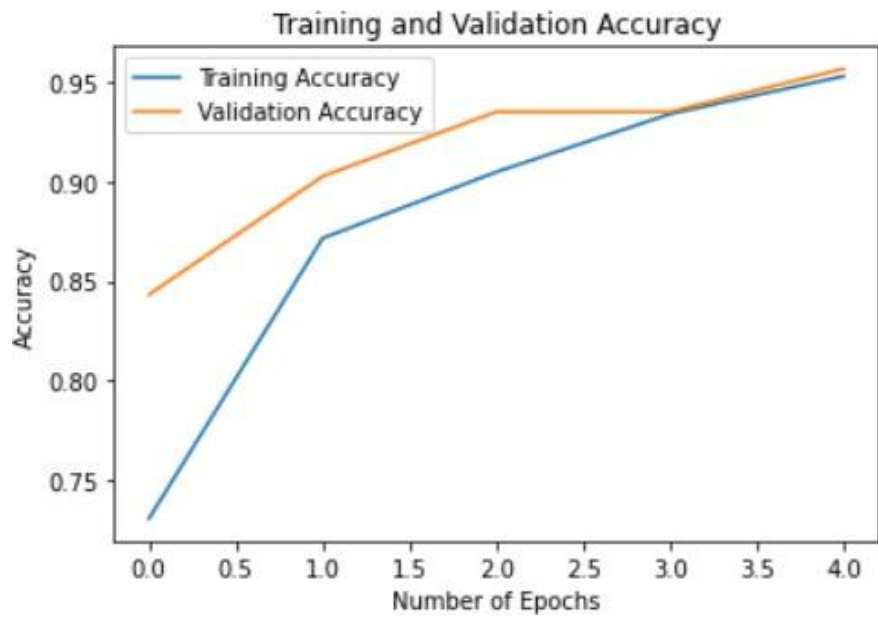


Fig 8: Training and Validation Accuracy over 5 epochs

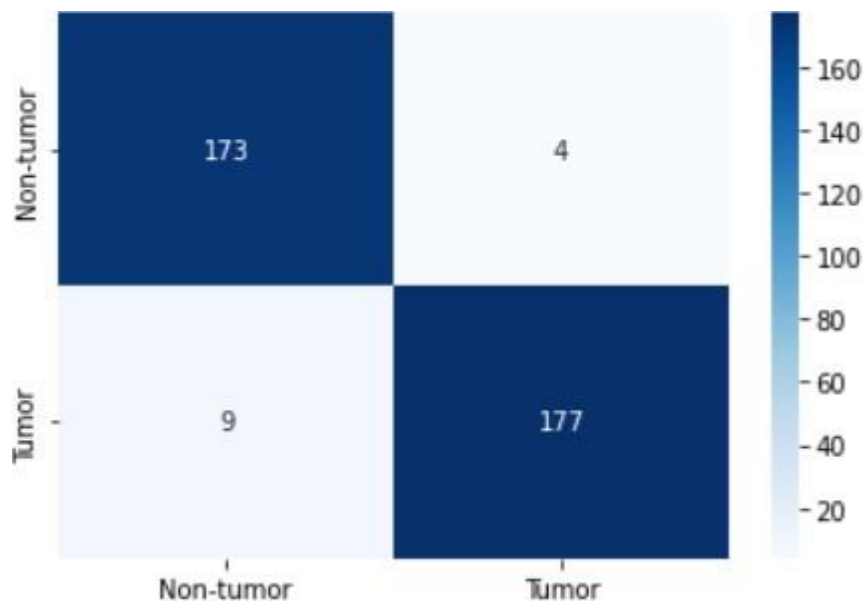


Fig 9: Evaluation metric: Confusion matrix

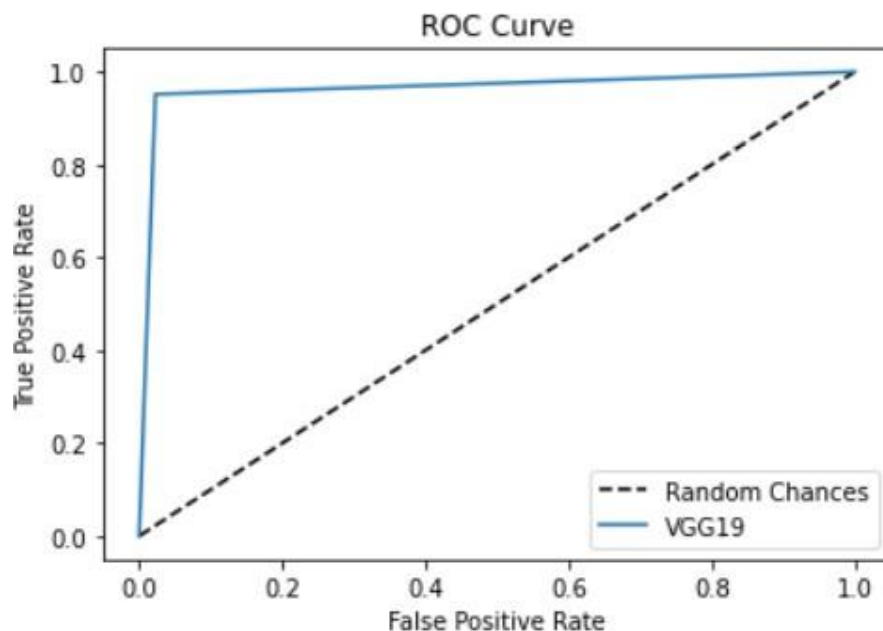


Fig 10: Evaluation metric: ROC Curve

9. Output and Visualization screenshots

```

Downloading data from https://storage.googleapis.com/tensorflow/keras
ls_notop.h5
80142336/80134624 [=====] - 17s 0us/step
80150528/80134624 [=====] - 17s 0us/step
Model: "sequential"

```

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None, 7, 7, 512)	20024384
dropout (Dropout)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dropout_1 (Dropout)	(None, 25088)	0
dense (Dense)	(None, 1)	25089
=====		
Total params: 20,049,473		
Trainable params: 25,089		
Non-trainable params: 20,024,384		

Fig 11: Training the VGG19 Model


```

Epoch 1/5
27/27 [=====] - 571s 21s/step - loss: 1.6904 - acc: 0.7307 - val_loss: 0.4781 - val_acc: 0.8432
Epoch 2/5
27/27 [=====] - 639s 24s/step - loss: 0.4379 - acc: 0.8716 - val_loss: 0.3344 - val_acc: 0.9027
Epoch 3/5
27/27 [=====] - 643s 24s/step - loss: 0.2645 - acc: 0.9049 - val_loss: 0.1602 - val_acc: 0.9351
Epoch 4/5
27/27 [=====] - 659s 25s/step - loss: 0.1963 - acc: 0.9340 - val_loss: 0.1752 - val_acc: 0.9351
Epoch 5/5
27/27 [=====] - 629s 23s/step - loss: 0.1292 - acc: 0.9530 - val_loss: 0.1206 - val_acc: 0.9568

```

Fig 12: Training 5 epochs

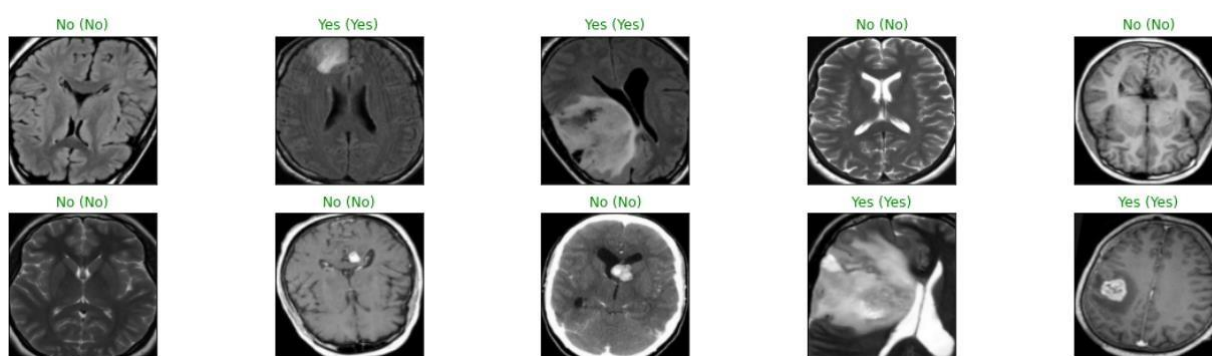


Fig 13: Output: Ground Truth V/s Predicted on random 10 images

10. Conclusion

We have successfully created a model that classifies MRI Scan Images. The accuracy of our model came out to be 96.4%. We employed a transfer learning-based approach, that is, VGG-19. VGG here stands for Visual Geometry Group. It is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. Our dataset initially did not have many images to work on. Thus, during pre-processing, we augmented the images in order to create a larger dataset and further cropped and resized the images for better accuracy of the model.

11. References in IEEE format

- [1] T. Kalaiselvi, S. T. Padmapriya, P. Sriramakrishnan, and K. Somasundaram, 'Deriving tumor detection models using convolutional neural networks from MRI of human brain scans', *Int. J. Inf. Technol.*, pp. 2–7, 2020, doi: 10.1007/s41870-020-00438-4.
- [2] Roy, S. S., Rodrigues, N., & Taguchi, Y. (2020). Incremental Dilations Using CNN for Brain Tumor Classification. *Applied Sciences*, 10(14), 4915. doi:10.3390/app10144915
- [3] Gokila Brindha, P., Kavinraj, M., Manivasakam, P., & Prasanth, P. (2021). Brain tumor detection from MRI images using deep learning techniques. *IOP Conference Series: Materials Science and Engineering*, 1055(1), 012115. doi:10.1088/1757-899x/1055/1/012115
- [4] Amin, J., Sharif, M., Gul, N., Yasmin, M., & Shad, S. A. (2019). Brain Tumor Classification based on DWT Fusion of MRI Sequences using Convolutional Neural Network. *Pattern Recognition Letters*. doi:10.1016/j.patrec.2019.11.016
- [5] Kalaiselvi, T., Padmapriya, S. T., Sriramakrishnan, P., & Somasundaram, K. (2020). Deriving tumor detection models using convolutional neural networks from MRI of human brain scans. *International Journal of Information Technology*. doi:10.1007/s41870-020-00438-4
- [6] Toğaçar, M., Cömert, Z., & Ergen, B. (2020). Classification of Brain MRI Using Hyper Column Technique with Convolutional Neural Network and Feature Selection Method. *Expert Systems with Applications*, 113274. doi:10.1016/j.eswa.2020.113274
- [7] J. Amin, M. Sharif, N. Gul, M. Yasmin, and S. Ali, 'Brain tumor classification based on DWT fusion of MRI sequences using convolutional neural network ☆', vol. 129, pp. 115–122, 2020, doi: 10.1016/j.patrec.2019.11.016
- [8] A. M. Sarhan, 'Brain Tumor Classification in Magnetic Resonance Images Using Deep Learning and Wavelet Transform', *J. Biomed. Sci. Eng.*, vol. 13, no. 06, pp. 102 –112, 2020, doi: 10.4236/jbise.2020.136010.
- [9] N. Poonguzhali, K. R. Rajendra, T. Mageswari, and T. Pavithra, 'Heterogeneous deep neural network for healthcare using metric learning', 2019 IEEE Int. Conf. Syst. Comput. Autom. Networking, ICSCAN 2019, pp. 1–4, 2019, doi: 10.1109/ICSCAN.2019.8878728.
- [10] K. Adu, Y. Yu, J. Cai, and N. Tashi, 'Dilated Capsule Network for Brain Tumor Type Classification Via MRI Segmented Tumor Region', in 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2019, no. December, pp. 942 –947, doi: 10.1109/ROBIO49542.2019.8961610.