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A Scientific Approach to Building an Image Classification model of brain MRI images for Brain Tumor detection

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Abstract:
The Computer associated-learning is one of the most significant achievements in the field of medical imaging. Generally, we use different technologies like computer tomography (CT scan) to diagnose disease or injury; in the lungs, liver, brain, etc. For this research, we have used MRI image datasets for the identification of Brain tumor classification and non-tumor classification. Tumors are generally abnormal growth; if this type of growth occurs in the brain is called a brain tumor. Early detection and proper treatment may reduce the chances of cancer. Computer vision is the domain where image features and classification extraction can be done very efficiently. In this research, automatic types of MRI image data sets can be considered using CNN (convolution neural network), i.e., VGG 16 architecture. With the help of a pre-trained model classifying and detecting brain tumors of an existing data set can be done. After augmentation volume of the data set can be improved and using individual augmentation values of each class also can be found. Experimental result shows that an accuracy of 97 % of an online data set can be seen.
Keywords - MRI, Brain Tumor, CNN, VGG 16, Image Augmentation, Image Classification, Quantification.

1. Introduction

The brain is the most critical organ in the human body. Uncontrolled cell division and abnormal cell formation in the brain are leading causes of brain tumors. Brain tumors, like other tumors, can be Benign and Malignant. Malignant tumors grow much more rapidly than the Benign tumors and frequently spread in the surrounding tissue [1] [2]. Benign tumors do not spread rapidly. Malignant tumors are considered cancerous. Primary brain tumors start in the brain; secondary tumors apply in the brain [3] [4].

A Brain tumor is the most deadly disease, so if this is not detected early, it can lead to cancer. So in this, we work on image classification techniques using CNN where we have two different classes, yes and no, denote tumorous and non- tumorous, respectively. MRI is the best imaging techniques that identifies the brain tumors. So this technique makes a huge impact on the medical image processing field. So finding out any deformities in the brain MRI is the best choice [5] [6]. The below Fig 1(a), Fig 1(b) and the Fig 2(a), 2(b) represents two different classes of MRI image dataset, i.e. class: yes, class: no. Class: yes depicts the brain MRI image having tumor and Class: no depicts the brain MRI image having no tumor.

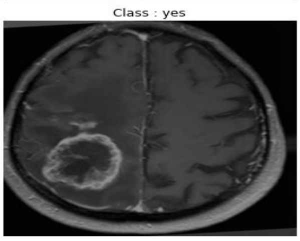

Fig 1(a)

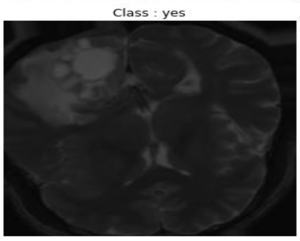

Fig 1(b)

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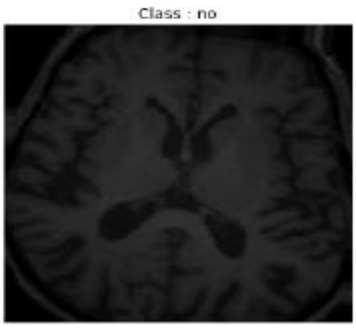


Fig 1(c)

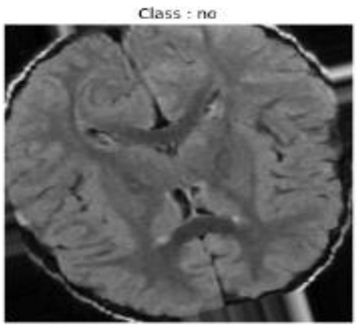


Fig 1(d)

CNN is a widely used feed-forward network used to classify image data sets very efficiently [7]. This network is used to handle a variety of inputs such that it ranks in a generic way. This CNN is used in medical image analysis [8].

VGG 16(Visual Geometry Group) is the CNN model which consists of 16 convolution layers [9]. It is structured and sequential. VGG 16 is a built-in image net dataset which is a collection of images almost 14 million images. The convolution layers used to detect the image border, image color etc.

Image Augmentation is the process of getting diversified data set [10][11]. It is the most important part of deep learning to increase the size of the data set.

Image Classification is basically used for image categories and differentiation between image classes [12] [13]. In this research we are having two distinct classes, Class: yes and Class: no, signify the availability of tumor and no tumor.

Quantification of image can determine the individual value of each existing data set can be found [14] [15].

In this research we have two distinct classes i.e. class: yes, class: no. that consists of different image online image data sets of presence of tumors and non tumors. After preprocessing the image data sets that particular Inputs can be feed in Machine for training and testing purpose .We use image augmentation for increase the volume of data sets to improve the accuracy of machine. Finally we quantize the image dataset of individual class sample value can be found.

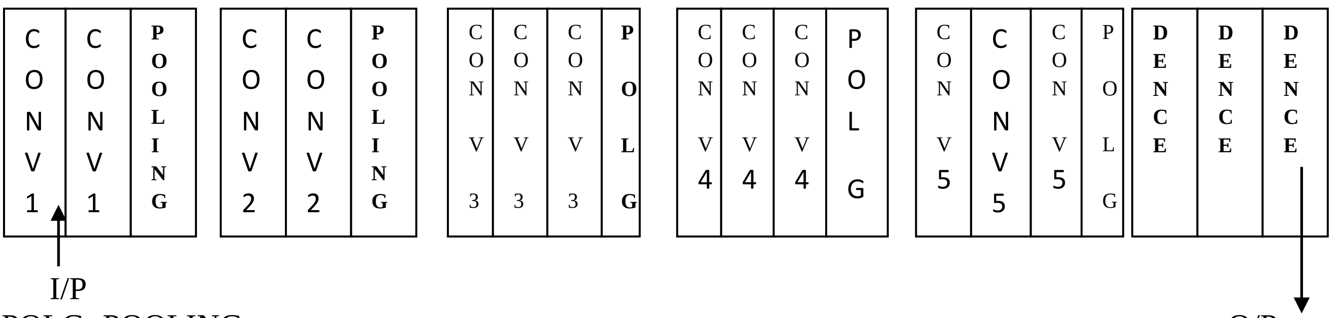
2. Experimental Methods or Methodology

2.1 Preprocessing the image data sets

Preprocessing increases the quality of the MRI images. It basically helps the medical professionals to locate the tumor efficiently. It sharpens the image quality that is very important for image classification.

Processing the MRI data set removal of noise can be done using Average Filtering techniques.

2.2 Image detection and Comparing between Existing data set using VGG 16.



POLG=POOLING O/P

Fig 2. VGG 16 Architecture

We are using VGG 16 architecture for object detection. Fig 2. represents VGG 16 architecture which is having 16 convolution layers which detects the object(MRI image) .

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2.3 Classification for the input data sets

We are using CNN for classification for the image data sets.

MRI input image data: I_p

test data: t_d, train data: t_r, $t_d > t_r$

if $I_p = (t_r + t_d)$ where $t_d > t_r$

yes categories: t_r, no categories: t_n

$I_p = (t_r + t_n)$

Fig 2. and Fig 3. represent the images having tumor visibility store in the 'yes' classification, no visibility store in the 'no' classification. We have two different classes for image classification.

Fig 3(a) **yes classification**

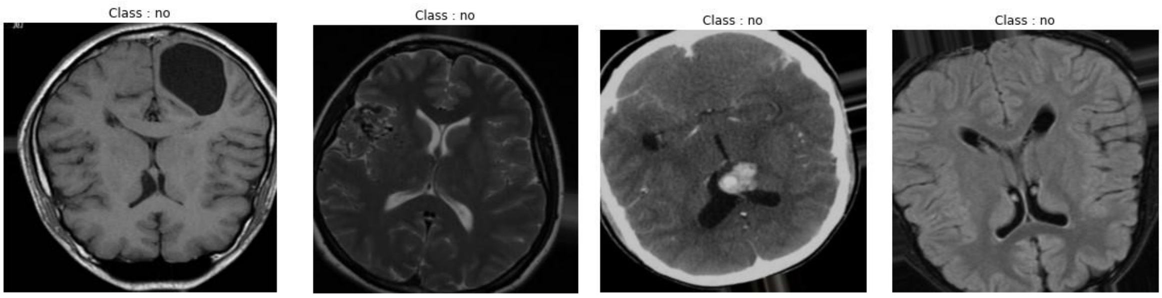

Fig 3(b) **no classification**.

2.4 Augmentation for image analysis:

We have done image augmentation technique to create this model to increase the volume of dataset. In classification we have found our machine level accuracy, after the augmentation that particular machine level accuracy is improved.

We know,

MRI input image data: I_p

test data: t_d, train data: t_r, $t_d > t_r$

if $I_p = (t_r + t_d)$ where $t_d > t_r$

yes categories: t_r, no categories: t_n

$I_p = (t_r + t_n)$

$I_y + r = (I_y + r) = A_{gy}$

$I_n + n = (I_n + n) = A_{gn}$

I_y = Yes class input data

I_n = No class input data

Where A_{gy} = Yes class dataset after augmentation,

A_{gn} = No class dataset after augmentation.

2.5 Quantification for image datasets:

We have done the quantification technique to get the accurate dataset of each class after applying the image classification and image augmentation technique. We have used this process to measure exact number of dataset of each class.

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We know,
MRI input image data: I_p
test data: t_d, train data: t_r, $t_d > t_r$
if $I_p = (t_r + t_d)$ where $t_d > t_r$
yes categories: t_r, no categories: t_n
$I_p = (t_r + t_n)$
$I_y + r = (I_y + r) = A_{gy}$
$I_n + n = (In + n) = A_{gn}$
Where A_{gy} = Yes class dataset after augmentation,
A_{gn} = No class dataset after augmentation.
I_q = Image quantification
I_{qy} = Image quantification of yes class.
I_{gn}= Image quantification of no class.
$I_{qy} = A_{gy}$
$I_{qn} = A_{gn}$
$I_q = (I_{qn} + I_{qy})$ where $I_q > I_p$

3. Results and Discussion:

In this part we are going to show and compare the accuracy of the model before and after applying augmentation. We are also going to show the image classification of our data set using VGG-16 model. In our model we have divided our dataset into two subcategories like testing data and training data. We have used 70% data for testing purpose and 30% data for training purpose.

Basic Dataset

Our dataset (Brain MRI image dataset) is consists of 253 MRI images which we are going to classified into two categories (tumor present also known as yes, tumor absent also known as no). We are using data augmentation technique for increasing data by using different parameters because we are working on a less number of data (155 in yes class, 98 in no class, after using image quantification). Instead of knowing the fact that we have a less number of data at our initial stage we started working on without augmentation, but the accuracy (93%) was not satisfied enough so that we applied augmentation to get much better accuracy (97%) than the previous work.

3.1 Classification using VGG-16

Fig 4(a) Image Classification

Fig 4(a) shows the classification of MRI input dataset. As the fig 4(a) shows that our dataset has been distributed into two classes, one is yes and another one is no. As we can see that the after distribution we got 62.3% in yes class and 38.7% in no class.

```
Epoch 30/30
12/12 [==============================] - 233s 20s/step - loss: 0.1276 - accuracy: 0.9382 - val_loss: 0.3504 - val_accuracy: 0.8933
```

Fig 4(b)**Data Accuracy before augmentation**.

Fig 4(b) shows the data accuracy before applying data augmentation, which is 0.9382

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Fig 4(c) Training & Validation accuracy and Training and Validation loss

Fig 4(c) shows training loss and accuracy as well as validation loss and accuracy.

The red line shows (in loss statistical graph) validation loss and the blue line shows training loss, we can see here that at the initial stage the validation loss is lower than the training loss but in the final stage the validation loss is higher than the training loss.

In the accuracy statistical graph at the initial stage validation accuracy is slightly higher than the training accuracy but at the final stage training accuracy is higher than the validation accuracy.

3.2 Augmentation of classified MRI input data set

	loss	accuracy	val_loss	val_accuracy
25	0.187601	0.915730	0.320883	0.853333
26	0.099910	0.966292	0.289579	0.893333
27	0.099922	0.971910	0.284683	0.866667
28	0.075389	0.971910	0.319351	0.826667
29	0.072739	0.977528	0.237995	0.880000

```
Epoch 30/30
12/12 [==============================] - 359s 30s/step - loss: 0.0727 - accuracy: 0.9775 - val_loss: 0.2380 - val_accuracy: 0.8800
```

Fig 4(d) Accuracy, Val_loss, Val_accuracy (after augmentation)

Fig 4(d) shows the accuracy, Val_loss, Val_accuracy of the augmented classified MRI input dataset. The val_loss is 0.2380, Val_accuracy is 0.88, accuracy is 0.9775

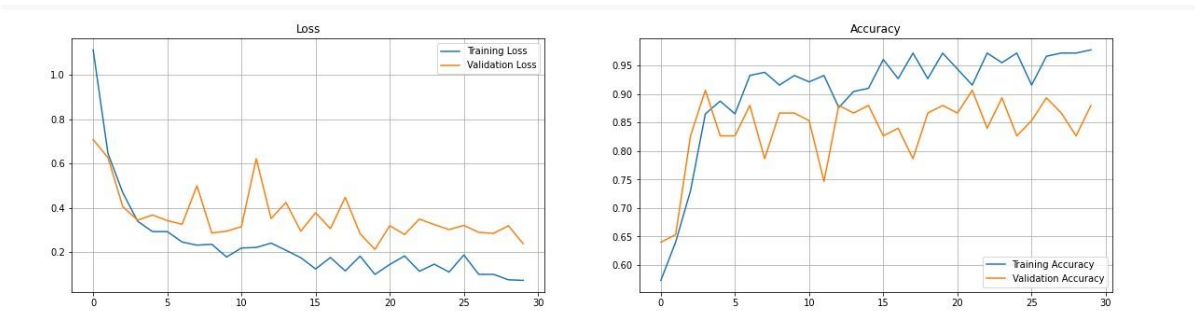

Fig 4(e) Training & Validation accuracy and Training and Validation loss (after augmentation)

Fig 4(c) shows training loss and accuracy as well as validation loss and accuracy (after augmentation).

The red line shows (in loss statistical graph) validation loss and the blue line shows training loss, we can see here that at the initial stage the validation loss is lower than the training loss but in the final stage the validation loss is higher than the training loss.

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In the accuracy statistical graph at the initial stage validation accuracy is higher than the training accuracy but at the final stage training accuracy is higher than the validation accuracy.

CONCLUSION

As per preceding research and findings, the classification of Brain MRI image is very important. Classified models can detect the tumor source and help medical professionals to identify them. It is already proved that early detection of tumors can prevent the chances of cancer. In this research with the help of computer vision using machine learning classification can be done. Using CNN of VGG 16 architecture the classification can be done and performed augmentation to increase the volume of the dataset. Image quantification can be done separately from the two classes. In the future to improve the machine level accuracy the comparison between different classifiers and also based on that design a new classifier will be done which helps to detect tumors at the early stage.

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