Data Augmentation Based Brain Tumor Detection Using CNN and Deep Learning

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***Abstract*—Brain tumor, always being under spotlight threatening human's life expectancy. The high chances of saving people from this life-threatening disease opens the gateway to our research of brain tumor detection. Magnetic Resonance Imaging (MRI) is being more efficiently utilized to easily identify the brain tumor. As this medical diagnosis branch of brain tumor detection has a very limited exposure to having datasets with larger sizes, the abundancy to implement Data Augmentation is also equally high. Data Augmentation stands to enrich the existing dataset and the common ways of augmentation are implemented. The implementation of Machine Learning/Deep Learning algorithms in the health industry has also increased exponentially greater over the years. Convolutional neural networks (CNNs) have been resonating in the application area with their DL approach. The research work supports the implementation of models such as VGG-16, ResNet-50, DenseNet121. Based on the results we obtain an efficient model is proposed for the detection of brain tumor.**

Keywords—Brain Tumor, ResNet-50, VGG-16, DenseNet-121, Magnetic Resonance Imaging, Convolutional Neural Networks, Data Augmentation.

I. INTRODUCTION

Over the past decade, annually millions have been diagnosed by brain tumors. [16] In 2020 alone, 308,102 people are diagnosed with brain tumours around the globe. Brain tumours is the primary reason for the increased death toll worldwide. To describe briefly, it is the development of abnormality in tissues of the brain or central spine. Though the actual reasons behind it are not yet known, exposure to radiation may increase the risk as well as genetics also play an important role. However, treatment in early stage increases the survival of patient which requires the identification of tumor in the beginning itself. Few models lack in detection of brain tumors from different locations of the brain and few lack to extract the features from the MRI images. The objective being to propose a model for better detection of tumor from MRI images which could facilitate the outcome to diagnose the tumors saving life of the patient. Computed Tomography (CT) scans and Magnetic Resonance Imaging (MRI) scans stand as the most prominent ways of scanning that assist in the brain tumour detection. Using these scans, we can successfully detect abnormalities in the brain. Through various methodologies, certainly, AI and deep learning, medical field has seen tremendous increase in accurate classification of brain tumours.

Availability of large data is not always possible; hence, the savior is augmenting the available data, using augmentation techniques. The chances of arising of the issue of overfitting is also high in this case. Overfitting problem can be efficiently tackled with the increase of the dataset size. The dataset enrichment can be done by augmentation techniques, these increases the available data by performing certain transformations such as width shift, rotate, zoom in and shear range, so on.

The agenda to improve the efficiency of existing models from the MRI images in detection of brain tumors stands still. The proposed research work's major goal is to enhance the size of dataset using data augmentation techniques, thus resulting in improved accuracy of models.

II. RELATED WORK

For our research, we looked at a few studies, some of which are included below.

Computed Tomography (CT) scan, Positron Emission Tomography (PET) scan, Magnetoencephalography (MEG) and Magnetic Resonance Imaging (MRI) were the major Imaging techniques that could assist any research work to the detection of tumors or any other diagnosis in the health industry.[8] supports the usage of MRI over other Imaging techniques for its varied modalities [9] [10]. The review article [1] contrasts the use of deep learning and machine learning techniques to extract features from MRI images with the use of classification over the collected data. They concluded that CNN models resulted in better accuracy. [2] A brief comprehensive description of how MRI methodology has been presented. The study also mentioned a highlighting point describing the unnecessity of usage of segmentation or any pre-processing algorithms as CNN [11] models are robust enough to complete the task without them. In the study of multiple degrading factors in MRI acquisitions, CNN models with less accuracy (AlexNet) have been recognized. The fact that AlexNet has its limitations as it has multiple varied sizes for its convolutional blocks,[12] VGGNet implements a constant size of 3X3 for its convolutional layers. This led to the motivation towards implementing the VGG16 model. [3] [13] Using the Brats-2015 dataset, implementing Weiner Filter for noise reduction, PF Clustering for segmentation and SVM for classification. KNN classifiers was the top-ranked with best results compared to other classifiers. [4][14] stated that Super pixels and Principal Component Analysis (PCA) played a vital role in extraction of features. As a result, brain tumors are detected accurately from Magnetic Resonance Images. The model, though precise, is not considered as an exemplary as the dataset information is not disclosed also leaving us with a detail of mere 40 image dataset usage.

[5] Supported the use of augmentation where the accuracy and learning rates of models increased significantly portraying the importance of augmentation. It also was successful in

solving the overfitting problem.[15] The implementation of hand crafted, and deep learning models for feature extraction and segmentation in [6] lead to the successful detection of tumors in the glioma region. The main drawback was it was only designed to detect tumors from the glioma region leaving aside meningiomas and pituitary tumors. The GrabCut method usage for segmentation showed few adversities as it has poor initialization. The model supported the famous dataset BRATS 2015–17. The research work [7] was based on ELM for feature extraction and the K-ELM for classification purposes. The model listed a high accuracy in detecting pituitary tumors but reported low accuracies in detection of tumors in meningioma regions.

III. Proposed Work

Use the subsequent stages to classify MRI images into having tumor or not using two CNN models-VGG16 and ResNet50 and a Deep Learning model-DenseNet, then compare the results of the models.

Step 1: Load Dataset consisting of Brain MRI images.

Using pandas, we are reading the dataset in this case. It has 3000 MRI images. The dataset consisting of two folders: 'yes' and 'no'. The first folder 'yes' is the one containing MRI images of brain with. Additionally, the second folder consists of images with no tumor.

Step 2: Perform Data Augmentation

In "Fig.1" we have displayed a sample of set of images that are augmented from the original image, which is displayed below as well. Though there are many augmentation techniques, rather than using the most common techniques, we used width shift, height shift, shear range and rescale. The purpose of using only these techniques is that they enhance the feature extraction from the images. For example, color brightness technique can be neglected as the MRI images are grayscale images.

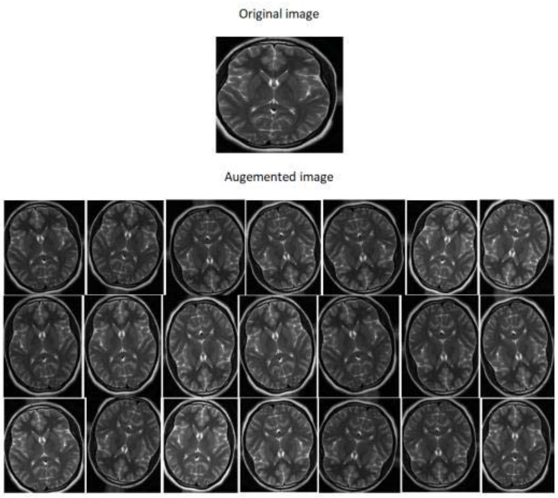

Fig. 1. Sample of augmented images

Step 3: Split the Data

The dataset must then be split into two sets with a ratio of 9 to 1(9:1) each: a training set and a validation set. We are dividing the data sequentially as opposed to at random since there is a significant problem with time. The split data of the dataset is split in such a way that it facilitates efficient training of the model.

Step 4: VGG16 Model Building for classifying MRI images

VGG16 convolutional neural network model is used to train the model and further to predict the images with tumor. Load the parameters of the model before making predictions. The model architecture involves 16 weighted layers. Finally, after the model training ends, the validation set validates and then the test data also takes part in measuring the accuracy of the model.

Step 5: ResNet50 Model Building for classifying MRI images

We will now use this data to train a ResNet50 implemented based on Residual neural network to predict the images with tumor. The model of 50 layers applied for model training which loads with parameters. The accuracy of the model is calculated at the end of the efficiency verification of the model.

Step 6: DenseNet Model Building for classifying MRI images

DenseNet121, a Deep Learning Model to predict the images with tumor. The model implements a total of 121 layers with convolution and average pooling layers working with the dense blocks. Finally, before the model training process starts, the mean squared error for the validation data is determined. Use the validation and testing data to analyse the model's performance.

Step 7: Comparison between the models

When compared between CNN models VGG16, Residual Neural Network ResNet50 and DenseNet121 which is a deep learning model. The comparison of accuracy between the models is based on the performance of models on augmented dataset which consists of 6000 MRI images.

A. Proposed Architecture

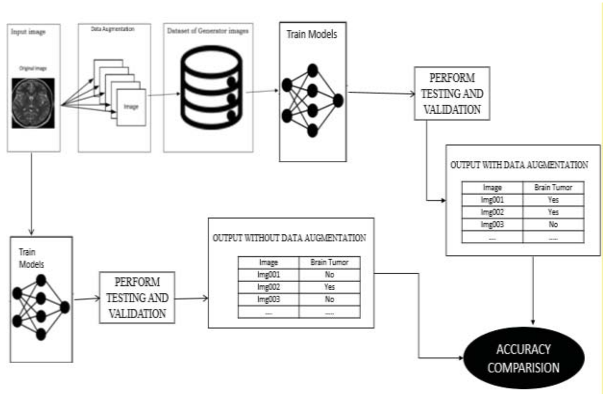

Fig. 2. Architecture Diagram for classifying MRI images.

The architecture diagram is shown in "Fig.2". The actions are as follows: First, consider a dataset with the two folders yes and no. To identify the trends, examine the dataset. Once the patterns have been discovered, perform data augmentation techniques to generate larger dataset of 6000 images approximately. Here, the accuracy is used to compare the models' performance.

B. Dataset Description

- The dataset we used is taken from Kaggle.
- The dataset contains two folders – Yes and No
- There are 3000 MRI images in the dataset.

- The first folder: 'yes' consists of 1500 brain MRI images having tumor.
- The second folder: 'no' consists of 1500 brain MRI images not having tumor.

C. Algorithm Description

ResNet-50

ResNet-50 is a Convolutional Neural Network Model. Coming to the implementation of the exact implementation to the ResNet50 architecture, this implementation goes as:

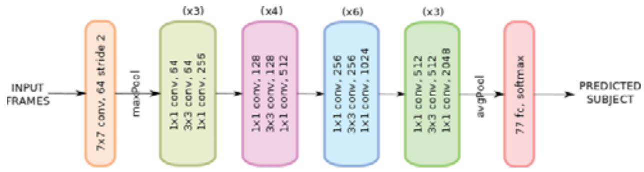

Fig. 3. Architecture Diagram for ResNet50

The input image must be of dimension 224*224*3. This is directed into the model which passes through the 1st layer, which is convolution layer. This model consists of layers with pretrained weights. It has less layers when compared to other models. Followed by some more layers to those we need to train with new weights for training the model with our dataset. The final classification of the image about which class it belongs to, is determined, and assigned here.

D. VGG16

The VGG-16 model is generally regarded as the model which substituted AlexNet correcting its drawbacks. The selection of VGG-16 over the other models for the research work is adequately discussed in [3]. VGG-16 model has been the most used model for its advantages over various other models, in terms of number of learning parameters and ease of training the model and so on. The name VGG-16, as it consists of 16 layers in its architecture. A set of input images of dimensions (224, 224, 3) are given in input layer. Two layers have 64 channels of a 3*3 filter size and max pool of stride 2 is applied.Next two are convolution layers of 128 filter size and max pool layer same as previous.Here after, there are 3 sets of 3 convolution layers and a max pool layer. One layer of 256 filters and the other two each of which has 512 filters of (3, 3) size. After this there are 3 fully connected layers, in which input is taken from last feature vector and outputs a vector. All the hidden layers use ReLu(Rectified Linear Unit) as its activation function.Finally, the images are classified in output layer.

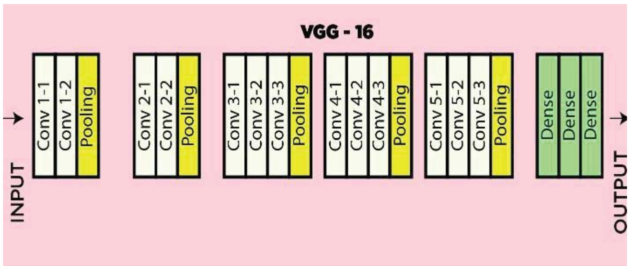

Fig. 4. Architecture Diagram for VGG16

E. DenseNet

DenseNet models anchor 121,169,201 and 264 layered architectures, our research work implemented the basic DenseNet121. In contrast to the ResNet design, DenseNet layers are relatively condensed and only add a tiny number of new feature-maps. In the model architecture, there are "dense blocks," where the size of the feature maps is fixed inside a block, but the number of filters varies between them. Four average pool layers and 120 convolutional layers make up the entire architecture. The fundamental pooling layer has a 3*3 maximum pool and a stride of 2, followed by a convolutional layer with 64 filters of size 7*7 in the first layer. The implementation of the thick blocks, which can support up to four of them, follows. Two convolutions in the Dense Block 1 are repeated six times each. One convolutional layer and one average pooling layer are blended to create Transition Layer 1. This is followed by the application of the Dense Block2 with its two convolutions repeated 12 times, the Transition Layer 2, the Dense Block3 with its two convolutions repeated 24 times, the Transition Layer 3, and finally the Dense Block4 with its two convolutions repeated 16. They all use one convolutional layer and one average pool layer as their transition layers. All of this is sent into a final global average pooling layer, which is applied, and which accepts all of the network's feature maps for categorization for output generation.

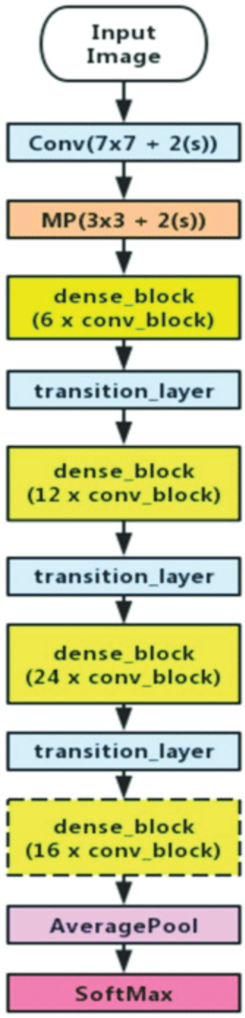

Fig. 5. Architecture Diagram for DenseNet121

IV. Experimental Results

This section summarises the findings of our study and contrasts the results of the two models in order to decide which model is the most effective at classifying MRI images.

A. Result Analysis

1) Results of the VGG16 model:

The model's performance is recorded with accuracy of 96.58 and reported a loss of 0.06665.

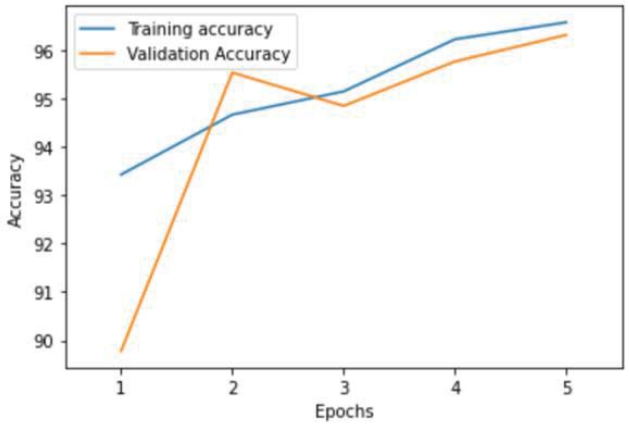

Fig. 6. Accuracy Plots Using VGG16

"Fig.6" shows the classification of 6000 MRI images using VGG16, with the Epochs as the X-axis and Accuracy plots on the Y-axis.

2) Results of ResNet50 model:

Analysing the performance of a CNN model using the validation data the accuracy is 98.70 also with a loss of 0.033.

The graph in "Fig.7" shows the classification of 6000 MRI images using ResNet50, with Accuracy on the Y axis and Epochs on the X axis.

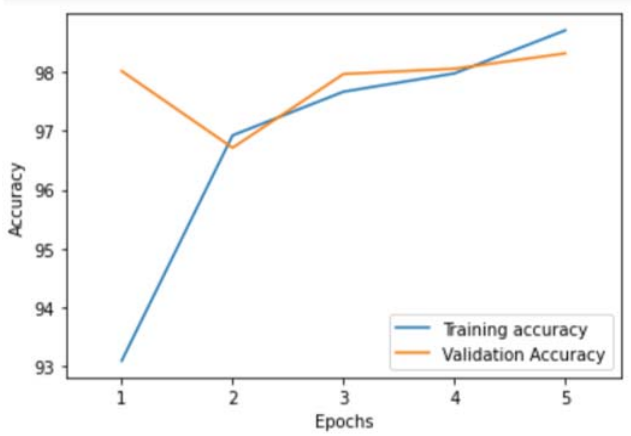

Fig. 7. Accuracy Plots Using ResNet50

3) Results of DenseNet model:

Analysing the performance of a CNN model using the validation data the accuracy is 99.50 also with a loss of 0.0240.

The graphic in "Fig.8" shows the classification of 6000 MRI images using DenseNet121, with Accuracy on the Y axis and Epochs on the X axis. It justified the plots of training accuracy and validation accuracy obtained after validation on the trained model.

According to our observations on the research work, DenseNet121 model has performed better than VGG16 and ResNet50 models in terms of accuracy. It clearly means that Deep Learning model has outperformed than CNN models.

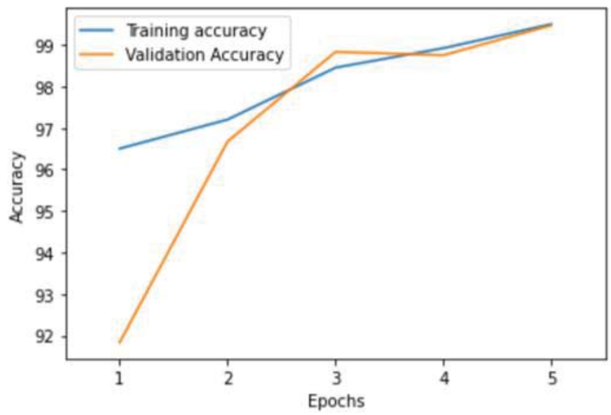

Fig. 8. Accuracy Plots Using DenseNet121

TABLE I. COMPARISION OF MODELS USING DIFFERENT METRICS

S.NO	Models	Accuracy	Loss	F1-score
1	VGG16	0.965	0.06665	0.8525
2	ResNet50	0.987	0.0330	0.9071
3	DenseNet121	0.995	0.0240	0.9451

VGG16's accuracy is 0.965, while ResNet50's is 0.987 and DenseNet121's is 0.995 are shown in "Table.1". We can infer that Deep Learning model performs better by comparing the accuracies.

Finally, we can say that the results of the Deep Learning based model –DenseNet121 is more significant than those of the other considered models. DenseNet121 rendered better results when compared under various metrics amongst the models.

V. CONCLUSION

Our study's major objective is to perform accuracy comparison between CNN and Deep Learning model when trained and tested on original dataset as well as the larger dataset resulted from augmenting the original dataset. Our study includes deep analysis of various CNN and Deep Learning architectures. We also found that these models performance gets effected based on the size of dataset. Thus, implementing augmentation techniques to overcome this problem. With our results, we can conclude that, model's performance in terms of accuracy has been increased, since with augmented data, model got the ability of high detection of features.

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