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Analysis of Brain Tumor Classification using Pre-Trained CNN models

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Abstract: Brain tumor detection is one of the crucial tasks in medical image processing. The difference between normal cells and infected cells is very less and almost both appear similar. So, the detection by the radiologist is inaccurate and there is a need for an automated system for brain tumor detection. This paper proposes an automated brain tumor classification system using 3D Magnetic Resonance Brain Images using Convolution neural network transfer learning concept. The transfer learning concept is used to modify or fine-tune the standard CNNs according to the user applications. This concept reduces the huge amount of input data requirements and minimizes the training and thus in computation time of the process. The top layers of benchmark CNN architectures like VGG16, ResNet 50, and InceptionV3 are fine-tuned and utilized for tumor detection. The performance of the CNN structures is analyzed in terms of performance metrics such as Accuracy, specificity, sensitivity, and various losses.

Keywords: Brain tumor detection, magnetic resonance imaging, convolution neural network, and Transfer learning

I. INTRODUCTION

Recently, Deep learning evolves as a major area for researchers, because of its high prediction accuracy and less error rate. Deep Learning algorithms/Structures perform better than humans, even in a huge volume of data. DL algorithms performance is parallel to the input data. So, we can say deep learning networks are data-hungry networks and we need a huge amount of data to make the network learn. The transfer learning concept introduced in Machine learning helps to utilize CNN applications with less available data.

Convolution neural networks are the advanced structure in Deep Learning and are designed especially for various image processing applications such as segmentation, feature extraction, and enhancement. The applications of CNN in medical image processing are mainly for the classification of cancer cells such as breast cancer, lung cancer, and brain tumor detection. The conventional automatic segmentation methods need a classifier with features which is a challenging task. CNN algorithm solves complex features such as healthy brain tissues and tumor tissues through multimodal MRI brain images. This paper discusses brain tumor classification from MRI Brain images.

The human brain does a complex job in controlling the other organs that work with billions of cells. A brain tumor occurs when an uncontrolled division of cells forms an abnormal group of cells around or inside the brain. These groups can affect the normal functionality of brain activity and destroy healthy cells (Kavitha et. al, 2016). Brain tumor classifies as grade I, grade II, grade III, and grade IV. Grade I and Grade II are termed as lower-grade (Benign). Grade III and Grade IV are termed as high grade (malignant). Benign tumors are nonprogressive (non-cancerous) so considered to be less aggressive, they originated in the brain and grow slowly; also, they cannot spread anywhere else in the body. However, a malignant tumor is cancerous because the cancerous cell grows rapidly in irregular boundaries. The tumor cells which originated in the brain itself is called a primary malignant tumor and the tumor cells originated in any other part of the body and spread to the brain are called a secondary malignant tumor (KhambhataKruti G et al, 2016, Kaur. G et al, 2016) The medical modalities are X-ray, CT (Computed Tomography) and MRI (Magnetic Resonance Imaging). MRI is one of the best imaging techniques that researchers use for the detection of brain tumors due to its high resolution and interpretation in images. So, it is used in brain tumor detection and treatment phases.

MRI images are more suitable for automatic brain tumor analysis because of their ability to provide a lot of information about the brain structure and abnormalities within the brain tissues due to the high resolution of the images [2,5]. Researchers presented different automated approaches for brain tumor detection and type classification using brain MRI images since it became possible to scan and load medical images to the computer.

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The paper is organized as follows. Section II provides the previous work done on brain tumor detection using CNN. Section III explains the concept of transfer learning and various benchmark CNN models. Section IV analyses the performance of the models defined using transfer learning with results and section V gives the conclusion.

II. Previous work

Segmentation is the major problem in brain tumor analysis. So, the diagnosis is required to find the brain cell abnormality or growth, and is very difficult to perform accurate delineation in radiotherapy. Since it is compulsory to avoid injury to the motor-sensory function places of the brain during therapy. Radiologist finds it difficult, during manual segmentation of brain tumors because of the complex structure of brain cells. However, an automatic algorithm of brain tumor segmentation plays a challenging task because of tumor size, shape, regularity, location, and heterogeneous appearance.

Recently several automatic segmentation methods have been implemented to detect MRI brain tumors. The detection is classified through a support vector machine (SVM) and random forest. These classifiers perform classification on the given data with the given features without doing the modification. But in another category of classifiers like CNN, the network extracts the features to do the specific task during training based on the task.

Presently deep neural network CNN is normally/commonly used in computer vision applications.

Brain tumor types and grades:

Benign brain tumor cells are non-cancerous cells and grow slowly. These cells spreading rate is rare to the brain cells. These cells cause problems when they start to press on some important areas of the brain.

Malignant brain tumors are cancerous cells. They intrude on healthy brain cells at different growth rates.

A. **Grades:**

Tumors are graded by how the cell appears normal and abnormal. The grading of the tumor cells is based on their spreading speed.

• **Grade 1:** The cells look nearly traditional and grow slowly. Semipermanent survival is possible.

• **Grade 2:** The cells look slightly abnormal and grow slowly. The neoplasm could unfold to near tissue and might occur later, perhaps at an additional grievous grade.

• **Grade 3:** The cells look abnormal and square measure actively growing into brain tissue. These tumors tend to recur.

• **Grade 4:** The cells look most abnormal and grow and unfold quickly.

The gliomas start in glial cells. Glial cells are the supporting structure of the brain and spinal cord. Astrocytoma is the usual type of gliomas.

Gliomas are classified into three types based on the glial cell.

B. **Glial types:**

Astrocytes: Tumors originating in these cells are named astrocytoma or glioblastoma.

Oligodendrocytes: The gliomas begin in oligodendrocytes cells are known as oligodendrocytes.

Ependymal cells: Tumors that start in these cells are called ependymomas.

C. **Tumor types:**

• **Astrocytomas:** These typically arise within the largest part of the brain, the neural structure. they'll be any grade. They typically cause changes in behavior.

• **Meningiomas:** This area unit is the foremost common primary brain tumor in adults. They are presumed to occur in the age of 70s or 80s. They arise within the meninx, the liner of the brain. They will be grade 1, 2, or 3 and typically benign which grows slowly.

• **Oligodendrogliomas:** These arise within the cells that create the covering that protects nerves. They are typically graded 1, 2, or 3 and grow slowly, and do not unfold to near tissue.

The various brain tumor segmentation techniques have been discussed as follows.

Rémi et al., (2018) proposed a method that classifies high-grade gliomas. They addressed Astrocytomas which were found commonly in adults and children.

Astrocytomas are classified into low-grade gliomas and high-grade gliomas. They improved the segmentation accuracy but the method needs a larger dataset for processing.

Dong et al (2017) proposed a diagnosis method based on a non-invasive magnetic resonance technique for brain tumor detection. A U-Net-based deep convolution network is used to classify the tumor from the non-invasive device outputs. The author used BRATS 2015 dataset. The dataset has unbalanced high-grade and low-grade gliomas.

Haveri et al., (2017) illustrated a brain tumor segmentation using deep neural networks to glioblastomas (both low and high grades) MRI images. It exploits both

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local and global features for tumor segmentation. The author uses the BRATS dataset for research work.

Hussian et al. (2017) suggested a segmentation algorithm using CNN to locate the tumor which has an irregular shape. The overfitting problem is minimized by adding max out and dropout layers in the batch processing. The authors also used pre-processing to remove unwanted noise in the input and post-processing using morphological operators to eliminate small false positives.

Kaiming et al. (2015) recommended a novel deep learning-based interactive segmentation framework. The proposed interactive segmentation uses CNN into a bounding box and scribble-based segmentation pipeline. The proposed CNN model is adaptive to a particular test image.

Cui et al. (2018) proposed an automatic segmentation based on cascaded CNN. The author added two subnetworks tumor localization networks (TLN) and an intratumor classification network (ITCN) in the cascade. TLN network separates brain tumor region from brain MRI images and the ITCN helps the separated tumor region into multiple sub-regions. The author used a multimodal Brain tumor dataset and the performance was measured by dice coefficient, positive predictive value, and sensitivity.

Khawaldeh et al. (2018) proposed an MRI brain tumor classification using Conv net and the architecture takes the entire image for execution. The network classifies brain tumor MRI images into low-grade and high grades tumor images. It uses Alex krizhousky network deep learning architecture.

Tonmoy et al. (2019) Analyzed the performance of traditional classifiers with CNN for brain tumor classification and proved that CNN is the best one and provides an accuracy of 97.87%. Heba et al. (2018) proposed a method for brain tumor classification by combining the fuzzy c means, DWT, and PCA with CNN. The brain MRI image is first subjected to segmentation using Fuzzy c means and the tumor affected region is segmented. Next DWT is used to extract the features from the segmented image and PCA is used to reduce the feature dimension. The obtained processed feature is then given to CNN for classification. All these processes so far discussed are having pre-processing steps like denoising, feature extraction, DWT decomposition, segmentation using fuzzy c means clustering before being applied to the CNN classifiers. So, the process is time-consuming and provides better accuracy after these pre-processing steps only.

The transfer learning-based CNN structures utilizes the pre-trained networks and improve accuracy without any pre-processing steps.

III. TRANSFER LEARNING-BASED BRAIN TUMOR SEGMENTATION

This paper analyses the performance of fully automatic segmentation of brain tumors using a convolutional neural network using the transfer learning concept. The suggested work accomplishes brain tumor segmentation using an anaconda framework with the TensorFlow backend for implementing high-level mathematical functions. Early detection of a brain tumor increases patients survival rate.

Transfer learning:

In transfer learning, a model trained using a large dataset, transfers its knowledge to a small dataset. So, the requirement of huge data problems is minimized and the network provides better accuracy with less amount input data. In transfer learning, a pre-trained CNN is used as a fixed feature extractor. The following are the steps in transfer learning:

- Take a pre-trained CNN architecture trained on a large data set (like ImageNet).
- Remove the last fully connected layer of this pertained network.

Thus, the remaining CNN acts as a fixed feature extractor for the new dataset.

The first one or two layers in the CNN are more generic and give general information. These layers transfer knowledge very well. Higher layers in this network are task-specific.

With this pre-trained CNN, connect the last layer (fully connected layer) according to the task such as classification, segmentation, etc., and train the last layer according to the task. Transfer learning and fine-tuning of higher layers often lead to better performance than training from scratch on the target dataset. In the proposed work, Imagenet CNN structures such as VGG16, InceptionV3, and ResNet50 are analyzed for brain tumor classification using transfer learning.

A. VGG16

VGG Net was the runner-up in the ILSVRC2014 architecture and is shown in Fig.1. The input of convolution layer-1 is of size 224x224 RGB image. The image is sent through a stack of convolution layers with a filter of 3x3 and a max-pooling with a 2x2 in the receptive field.

The small receptive field is more suitable to capture the notion of left/right, up/down, center image details. It has only 3×3 convolution but many filters. Because of its architectural uniformity, it is the most appealing network for

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feature extraction from images. The weighted configurations of this architecture were made public and are have been used as the baseline for many applications and challenges as the feature extractor. VGG net is in two types: VGG16 and VGG19. The number followed by VGG denotes the number of layers in the network. Here, we have taken VGG16 for the analysis.

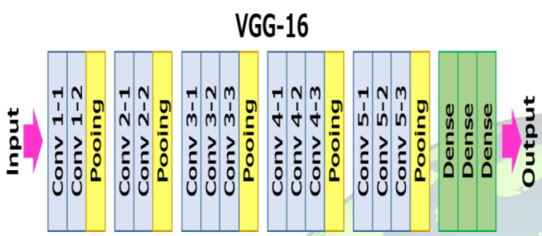

Fig 1. VGG16 Architecture

B. **ResNet50**

ResNet 50 Convolutional Neural Network has 50 layers and is most popularly used for image classification. Skip connections /Identity connections in the network is a shortcut connection that Skips one or more layers in the forward path as shown in Fig.2. Skip Connections are used to explicitly copy features from earlier layers (lower layers) into later layers (Higher layers). This improves in extracting more fine information from higher layers. This ResNet structure is mainly used to minimize the vanishing gradient problems in CNNs.

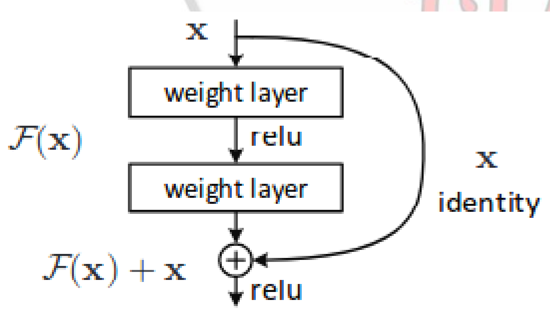

Fig.2. ResNet structure

Wang et. Al (2018) proved that residual networks (ResNet) are easy to optimize and can gain considerable accuracy when compared to plain networks for image recognition.

C. **InceptionV3**

The important milestone in CNN development is the Inception network.

Before Inception, researchers tried to improve the performance of CNN by just stacking convolution layers. The network structure was more complex to improve the performance in terms of accuracy and speed. The network has several inception modules with multiple size convolution layers as shown in Fig.3. The inception module contains popular versions of Inception as follows.

- Inception V1
- InceptionV2
- Inception V3
- InceptionV4
- Inception ResNet.

Each version is a reiteration betterment of the previous one.

This structure uses filters of multiple sizes that operate on the same level. The Naïve inception computes convolution using three different sizes of filters, max pooling is performed on the output of each convolution module. The concatenated output of all the modules is sent to the following inception module.

Inception V2 network computes 5x5 convolution as two 3x3 convolution operations to enhance speed. The 5x5 convolution speed is 2.78 times greater than the two 3x3 convolution speeds. The network computes convolutions of filter size nxn as two convolutions of 1xn and nx1 combination and thus leads 33% cheaper than the single nxn convolution. Inception-v3 has 48 layers deep network.

Features of InceptionV3

- Computes 7x7 convolutions.
- BatchNorm in the Auxillary Classifiers.
- RMSProp Optimizer
- Prevents overfitting with the help of a regularizing component and label Smoothing.

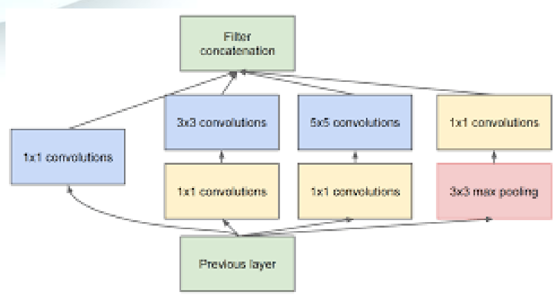

Fig 3. Inception module

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The workflow of CNN models based on transfer learning

1. Importing pre-processing libraries.
2. Import data.
3. Data Resizing
4. Data Augmentation.
5. Loading Benchmark CNN Structures.
6. Modifying the top layer - fully connected layer according to the tumor classification process.
7. Build and compile the model.
6. Model training and testing.
7. Analysis of model performance metrics

The process is implemented in the Keras -TensorFlow platform. First Keras sequential model and pre-processing function like image data generator are imported.

The Brain Tumor Kaggle dataset is used for the analysis and it contains 253 brain MRI images with two classes: Low-grade tumor (tumor No category) and high-grade tumor (yes) category and are taken from Kaggle. The training and testing datasets have different numbers of images in the tumor: yes and no categories. The input image is resized to 224x244 size according to the fixed input size of pre-trained models. The data augmentation is done for the training set to improve accuracy and eliminate the overfitting problem.

The data augmentation was done as follows.

- rescale=1/255
- shear_range=0.2
- zoom_range=0.2
- horizontal_flip=True.

All the pre-trained models are imported from Keras. applications.layers library as follows.

- from keras.applications.resnet50 import ResNet50 (for ResNet50 model)
- from keras.applications.inception_v3 import InceptionV3 (for InceptionV3 model)
- from keras.applications.vgg16 import VGG16 (for VGG16 model)

The models are loaded with an ImageNet weight matrix. The top layer of the pre-trained networks is removed and a Fully connected layer with two outputs is sequentially added to the model for tumor classification. The model is used as it is without training except for the last layer (output layer). Next, the model is compiled with Adam optimizer and categorical cross-entropy loss function. The model is allowed to fit the given training and testing data. The training accuracy and validation accuracy of the models are measured for 10 epochs.

IV. Performance analysis of Pre-Trained Models

The various pre-trained models and their total number of parameters are given in table-1. The VGG 16 has less trainable parameters when compared to the other two models. The number of trainable parameters is approximately only 25% when compared to the ResNet50 and 50% for InceptionV3. The total number of parameters is around 14 million in VGG16. The total number of parameters in ResNet 50 and InceptionV3 are around 21 million and 23 million, respectively. The model losses are also measured for 10 epochs and the values are tabulated.

The various model accuracy performance is compared in table2. The training accuracy of the VGG16 model is 93.6% and it almost follows the validation accuracy. The training accuracy of InceptionV3 is slightly less than VGG16 and it gives a small variation in training and validation accuracy. The accuracy of ResNet 50 is higher than the other two models but there is a deviation in the validation accuracy when compared to its training accuracy. The computation time of the models is also given in table-2. The algorithm is implemented using a PC with AMD PRO A12 98008 R7 Processor frequency 2.7 GHz and 8GB RAM capacity. The time for Inception V3 is less when compared to the other two models.

TABLE I
PRE-TRAINED MODELS WITH THE TOTAL NUMBER OF PARAMETERS

S.No	Pre-trained model	Total No. of parameters	No. of trainable parameters
1	VGG16	14,764,866	50,178
2	InceptionV3	21,905,186	1,02,402
3	ResNet50	23,788,418	2,00,706

TABLE III
MODELS TRAINING AND VALIDATION ACCURACY WITH COMPUTATION TIME

S. No	Pre-trained model	Training Accuracy	Validation Accuracy	Computation time
1	VGG16	93.6%	94.07%	3061 seconds (51 minutes)
2	Inception V3	92.89%	86.21%	1322 seconds (22 minutes)
3	ResNet5 0	98.42%	38.74%	2480 seconds (41 minutes)

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The accuracy plots of the three models for 10 epochs are shown in Figures 4,5 and 6.

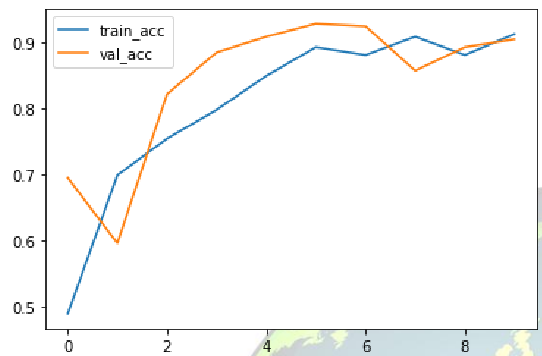

Fig 4. Training and Validation accuracy plot of VGG16 Pretrained model

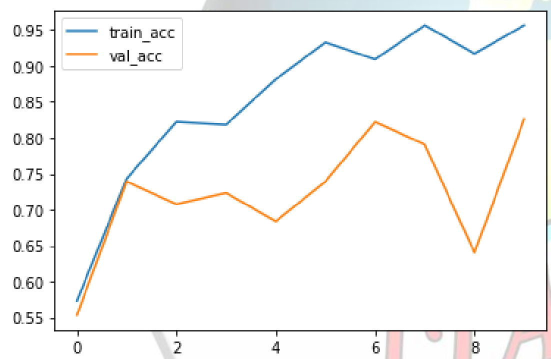

Fig 5. Training and accuracy plot of InceptionV3

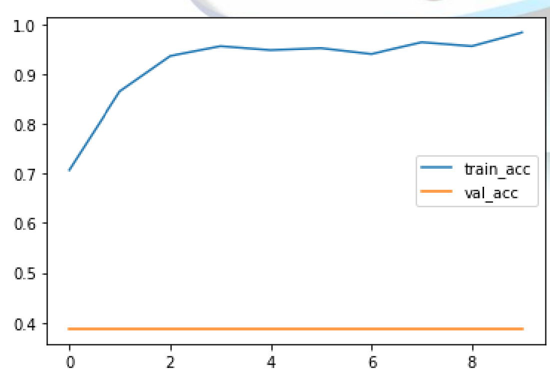

Fig 6. Training and Validation accuracy plot of ResNet50

The ResNet 50 model's sample input and output MRI Images (Predicted images) are shown in Figures 7 and 8 respectively. The model correctly predicts the brain tumor as a yes or no category with 98.42 % accuracy.

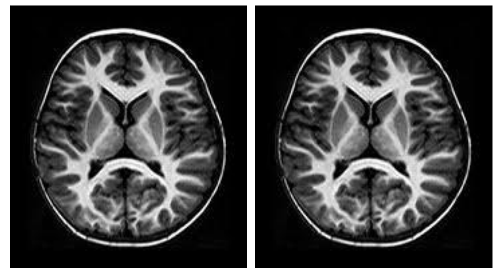

Fig.7.Input brain Image without tumor and output predicted as no (low grade)

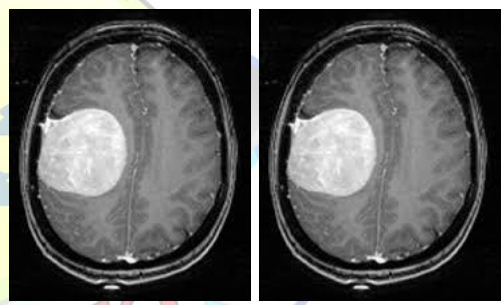

Fig 8. Input brain Image with tumor and output predicted as yes (High grade)

V. CONCLUSION

The pre-trained models like VGG16, InceptionV3, and ResNet 50 were analyzed for brain tumor classification. It classifies the brain MRI images into two categories as low grade and high grade. The accuracy of ResNet50 is high when compared to the other two models with high computation time. The prediction accuracy is a high priority in medical image processing when compared to other parameters like computation complexity, network size, etc., Transfer learning saves model training time and improves accuracy with fewer input data conditions.

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BIOGRAPHY

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