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Brain Tumor Classification from MRI Images Using Pretrained Deep Convolutional Neural Networks

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Abstract: Brain tumor is an abnormal tissue growth which may lead to cancer and it is characterized by the excessive cell proliferation in certain parts of the brain. One of the current reliable technologies that may be employed to identify brain tumor is to apply Magnetic Resonance Imaging (MRI) scans. The scanned MRI images are then monitored and conventionally examined by the medical specialists to observe the existence of tumor. As the number of people suffering brain tumor is very much increased and their corresponding mortality rate has reached 18,600 in the year 2021, research on devising more effective and efficient tools to assist the medical specialists on the identification of brain tumor is considered very urgent. In the previous studies, the Convolutional Neural Network (CNN) based models demonstrate their capability to detect brain tumor with 96% classification accuracy and they are found to be more reliable than other machine learning based models. In an attempt to obtain the best classification accuracy on both binary and multi-class MRI brain images, some powerful pretrained deep CNN models namely VGG16, VGG19, ResNet50, ResNet101, and InceptionResNetV2 are computationally experimented using publicly open MRI datasets. State of the art accuracy of the pretrained models is achieved by fine tuning the parameters of the convolutional layers of the base models and followed by feeding the high-level feature maps extracted from each corresponding base model either into flatten layers or into global average pooling layers prior to classifying the tumor by fully connected layers. The highest testing accuracy score as high as 99% is achieved by the VGG16 and InceptionResnetV2 on binary MRI image classification and a little higher than 99% is obtained by all the pretrained models on multi-class MRI brain image classification.

Keywords: *Brain tumor, convolutional neural networks, detection and localization, MRI scans, pre-trained model.*

1. Introduction

Brain tumor is an abnormal tissue growth and it is characterized by the excessive cell proliferation in certain parts of the brain. The number of new cases on brain tumor is estimated 24,530 cases and the corresponding mortality rate has reached 18,600 in the year 2021. In the meantime the average life expectancy of a person affected by this disease up to 5 years is only 32.6% [1].

The identification of the existence of brain tumor is not a straightforward task due to the fact that symptoms experienced by people with brain tumor tend to lead to mental illnesses such as anxiety and depression. In consequence, in the early stages they will usually be diagnosed as people with mental disorders even though the patient should have had a brain tumor [2]. Prior to the diagnosing step, by using one of the current reliable technologies brain tumor patches are first captured with the help of magnetic resonance imaging (MRI) scans. The scanned MRI images are then monitored and examined by the radiologists and other medical specialists to check if the tumor is presence. Thus, to get a decision on whether a patient is indicated for a brain tumor or not, it probably takes some time because it requires a thorough analysis from a medical expert team capable of reading and identifying tumor from a collection of MRI images. Moreover, due to the nature of the complexity of the MRI images, the detection of the existence of brain tumor can be sometimes led to a false negative decision. Therefore, in order to overcome the aforementioned critical drawbacks, high-speed computers with machine learning paradigm may be required by the medical team not only to speed up the whole process of identification but also to make a more precise decision on brain tumor detection and localization.

With the emergence of the convolutional neural networks (CNN) methodologies, the image features are automatically extracted and the learning process is carried out more deeply. CNN offer much better detection accuracy compared to the ordinary machine learning based approaches. Cinar and Yildirim [3] conducted an experiment using CNN based model to classify MRI brain images and their model is able to achieve 97.2% detection accuracy. In their study, they propose a new CNN architecture inspired by ResNet50 with the top 5 layers are removed and replaced with 8 new layers.

Mzoughi, et. al. [4] employ Deep Multi-Scale 3D CNN to classify 2 classes of brain tumor namely low-grade gliomas (LGG) and high-grade gliomas (HGG). Their model succeeded to get detection accuracy up to 96.49% on Brain Tumor Segmentation (BraTS) 2018 datasets. Further, Bhanothu, et. al. [5] classify MRI brain images consisting 3 classes of tumor, namely glioma, meningioma and pituitary. Their algorithm that extracts the high-level feature maps from VGG16 base model uses Fast R-CNN as a classifier. This study achieves mean average precision of 77.6% for all classes. Following Cinar and Yildirim [3], Kumar, et.al. [6] proposed ResNet50 based CNN model to overcome the vanishing gradient and the overfitting problems. Employing 3064 MRI brain

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images, Kumar, et.al reported that the model is able to achieve 97.48% classification accuracy. Qodri, et.al [7] performed brain tumor classification using pre-trained deep CNN models namely ResNet50, NASNet, XceptionNet, and VGG16 on MRI open dataset containing 253 images, 155 of which are tumor images.. The findings of their study indicate that both ResNet50 and VGG16 models are capable of achieving accuracy score up to 96%. The outcome shows that pre-trained models with their associated transfer learning could be used to significantly improve the accuracy of the MRI brain image classification.

In an attempt to obtain the best classification accuracy on both binary and multi-class MRI brain images, in this study we perform an experimental computation on publicly available brain tumor datasets using some powerful pretrained deep CNN models namely VGG16, VGG19, ResNet50, ResNet101, and InceptionResNetV2. State of the art accuracy of pretrained CNN models is achieved by fine tuning the parameters of the convolutional layers of the base models and followed by feeding the high-level feature maps extracted from each corresponding base model either into flatten layers or into global average pooling layers prior to classifying the tumor using fully connected layers.

2. Pretrained Deep CNN Models

Pretrained CNN models are models that have been trained using 1.2 million of training images with 50,000 and 100,000 images for validation and testing respectively. As the trainings were carried out in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), all the CNN models involved in the challenge are then called ImageNet pretrained models. The models are expected to have the capability of recognizing 1,000 different objects encountered in everyday life. Through the use of transfer learning scheme, the models may then be used for various computer vision tasks and they do not need to train from scratch whenever they are required to recognize a brand-new object in the future. Moreover, using such a transfer learning, even though the training involves only a relatively small number of datasets a remarkable good classification accuracy still can be obtained. Powerful ImageNet CNN models have been publicly available for some time and some of them are VGG16, VGG19, ResNet50, ResNet101, and InceptionResNetV2.

2.1. VGG

The general trend of developing CNN based models is actually to make deeper and more complicated networks in order to achieve higher detection accuracy and the VGG is one of them. Simonyan and Zisserman [8] as the winning team on the 2014 ILSVRC challenge shown a significant improvement on the prior-art-configurations by pushing the depth of the convolutional block to 16-19 convolutional layers with only using small 3x3 convolutional filters

The VGG16 architecture consists of 13 convolutional layers each with rectified linear unit (RELU) activation function, 5 maximum pooling layers, and 3 fully connected layers as a classification block. In the classification block, the first two layers consist of 4096 channels each and in the last layer contains 1,000 channels with softmax activation function [8]. The VGG16 and the VGG19 is distinguished by the number of the convolutional layers employed in the convolutional blocks. As is shown in Figure 1, the VGG19 employs 16 convolutional layers instead of 13 layers, The entire kernel used in the VGG architecture is of size 3 x 3 and the maximum pooling layers of size 2x2 with stride 2 are used to down sample the input image. If the RGB image of size 224x224x3 is set as the standard input to the VGG16 convolutional networks, the final size of the down-sampled and filtered image will be of size 7x7x512 prior to entering the classification block.

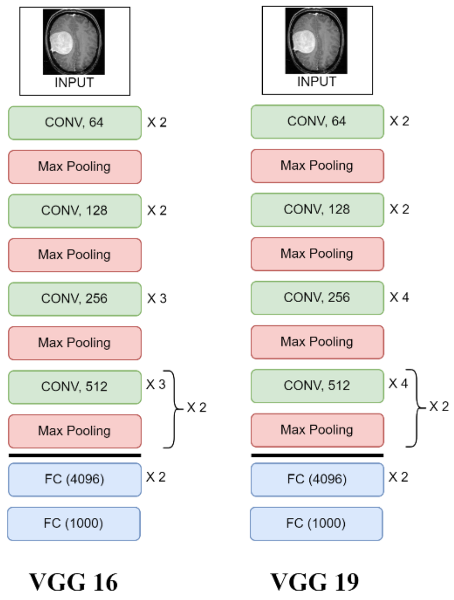

Figure 1. Basic block diagrams of VGG16 and VGG19 architectures

2.2. ResNet

Increasing the depth of the network by simply stacking the convolutional layers together does not gurantee the networks performance becomes better. Deep networks are somewhat hard to train due to the vanishing gradient problem. As the gradient is back propagated to the very beginning of convolutional layers, the very deep networks performing so many repeated multiplication may make the gradient infinitively small. As a result, as the network goes deeper, its performance gets saturated or even starts degrading rapidly.

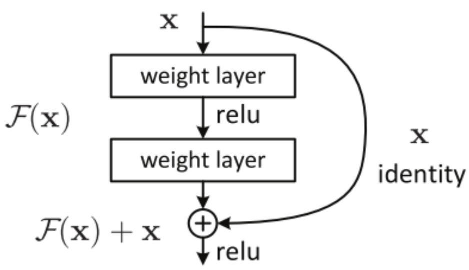

Figure 2. ResNet residual block

In order to overcome the aforementioned vanishing problem, Zhang, et.al [9] introduce what is so called “identity shortcut connection” that skips one or more layers, as shown in Figure 2. They believe that by applying shortcut connections, the skipped layers will behave exactly like identity layers that do not do anything and the performance of the networks will not be degraded.

Zhang, et.al [9] further argue that using such a residual network (ResNet), it is possible to train hundreds or even thousands of layers without losing the compelling performance of the networks. The ResNet50 is a variant of ResNet having 50 convolutional layers that skip every 3 layers as the residual building blocks. Resnet uses RELU activation functions on its building blocks.

2.3. InceptionResNetV2

It is undeniable that ResNet put very much influence on the development of the Inception architecture originally created to have a good performance at relatively low computational cost. ResNet that applies residual connections within a more traditional architecture has succeeded to achieve state of the art performance in the 2015 ILSVRC challenge. The InceptionResnetV2 is a variation of the InceptionV3 model that combines the architecture of the InceptionV3 with residual connections introduced by the ResNet [10]. This hybrid deep CNN model has the advantages of a residual network and retains the unique characteristics of the multi-convolutional core of the Inception network. Zhang, et.al [9] show that residual connections are implicit approaches for training very deep architectures. This improved version of the Inception architecture significantly improved performance and accelerated the model. Figure 3 shows the basic block diagram of InceptionResNetV2.

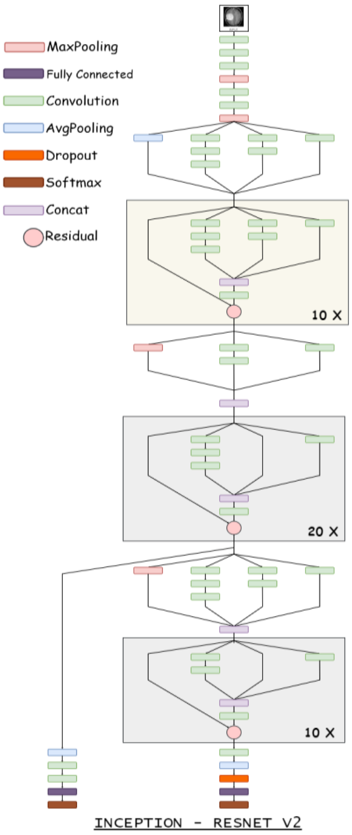

Figure 3. Basic block diagram of InceptionResNetV2

3. Experiment and Result

3.1. MRI Brain Tumor Datasets

In this study two brain tumor datasets collected from Kaggle are employed. The first dataset is BraTS 2019 dataset available in 2 folders. The first folder contains 2800 images, 1400 of which are brain images with tumor. The second folder of BraTS 2019 contains 200 brain images with 100 of which are tumor images. The typical MRI scan of brain images of size 512x512x3 pixels is shown in Figure 4. The second MRI brain tumor dataset comes

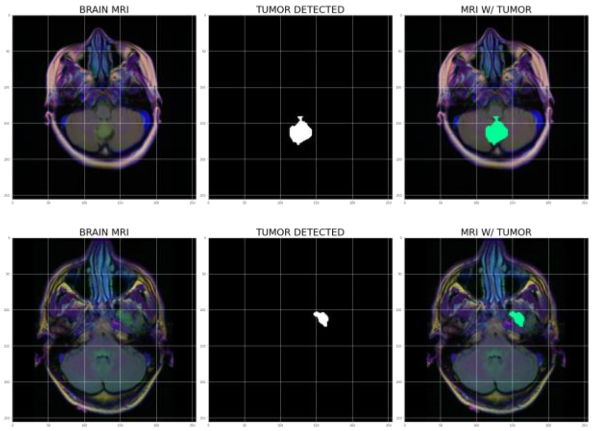

Figure 4. Sample of MRI brain images

with 2 main folders, training and testing folders. The training folder containing 5712 brain images consists of 1321 glioma, 1339 meningioma, 1457 pituitary, and 1595 normal images. Meanwhile the testing folder containing 1311 brain images consists of 300 glioma, 306 meningioma, 300 pituitary, and 405 normal images respectively. The binary classification of MRI images will then be performed on the BraTS 2019 dataset as it only consists of two classes of image namely tumor and no-tumor images. In the meantime, the second dataset as it contains four classes of brain images (glioma, meningioma, pituitary, and normal) will therefore be used for MRI image multi-class classification.

3.2. Result and Discussion

The performance evaluation of the powerful pretrained models is experimented on the Python Google Colab Pro environment accelerated by Graphic Processing Unit (GPU) and 25 GB of RAM. As it is shown in Figure 5, the whole experiment is facilitated by the ImageNet pretrained models of shape 224x224x3 with which the further training of the CNN models is carried out without having to start from scratch. Using such a transfer learning a remarkable performance on various image classification may easily be achieved. As already mentioned, to further improve the

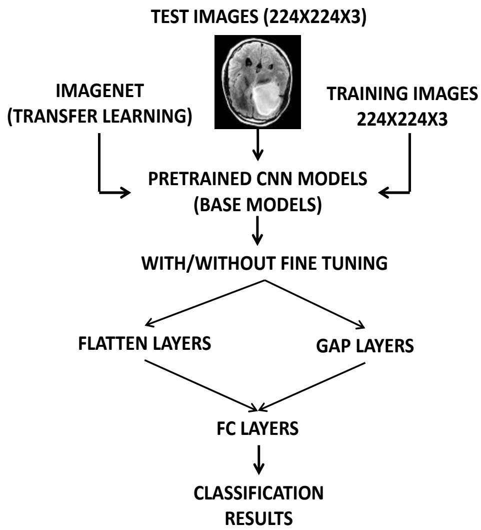

Figure 5. Computational experiment setup

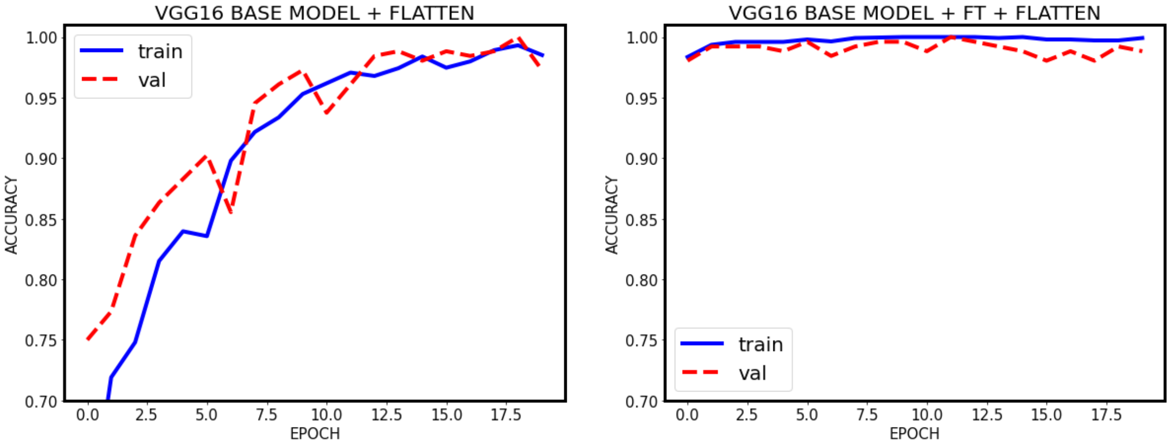

Figure 6. Performance of pretrained VGG16 model on binary MRI images before (left) and after (right) fine tuning

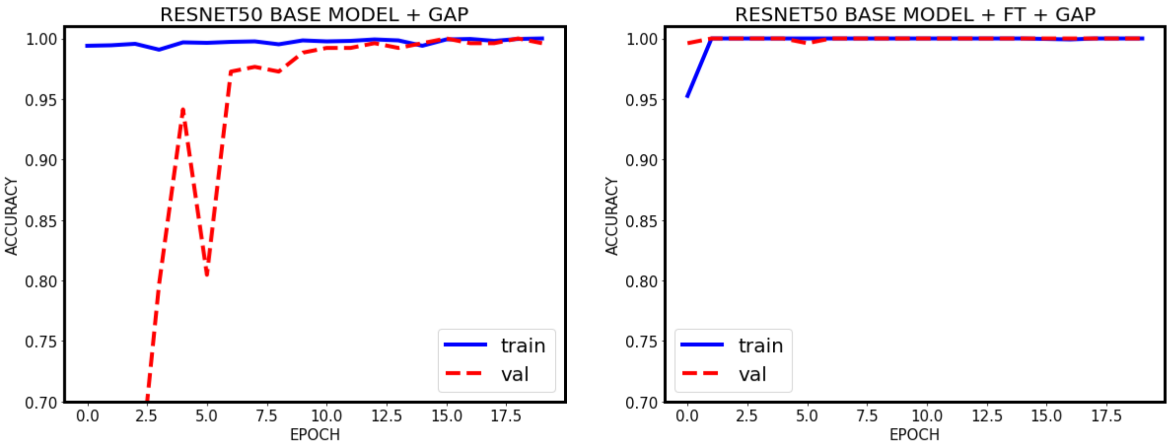

Figure 7. Performance of pretrained ResNet50 model on binary MRI images before (left) and after (right) fine tuning

Table 1. Performance summary of 5 pretrained CNN models on binary MRI images

PRETRAINED MODELS	*FLATTEN*		*FINE TUNED + FLATTEN*		*GAP*		*FINE TUNED + GAP*	
	VALID	*TEST*	*VALID*	*TEST*	*VALID*	*TEST*	*VALID*	*TEST*
VGG16	99.6	98.0	100.0	99.0	98.2	96.5	98.5	98.0
VGG19	99.9	98.0	100.0	97.5	99.6	97.5	99.3	98.0
RESNET50	100.0	98.0	100.0	98.0	100.0	97.0	100.0	98.5
RESNET101	100.0	95.0	100.0	98.5	99.6	98.0	100.0	98.0
INCEPTIONRESNETV2	100.0	98.0	99.6	99.0	99.6	97.5	100.0	97.5

performance of the pretrained models the weight parameters in the base model are fine-tuned by unfreezing a few of the top layers and followed by extracting the high-level features maps from the corresponding base model prior to feeding them either into flatten layers or into global average pooling layers.

MRI training dataset of size 224x224x3 each is input into the pretrained model along with the corresponding ImageNet of the same size. The computational experiment is then performed on four types of configurations namely (1) base model (BM) + Flatten + Fully-Connected (FC) layers, (2) BM + fine tuning (FT) + Flatten + FC, (3) BM + Global Average Pooling (GAP) + FC, and (4) BM +FT + GAP + FC respectively. Employing different initial learning rate, 10^{-5} for fine-tuned configurations and 10^{-4} for configurations without fine tuning, we succeed to achieve remarkable training, validation, and testing accuracies on all of the pretrained CNN models. Figure 6 and 7 show training and validation accuracy of VGG16 and ResNet50 models for binary classification before and after fine tuning the parameters of the certain convolutional layers of the base models. It is very obvious that both pretrained models are able to further improve the training and validation accuracies on BraTS 2019 dataset after applying the fine-tuning strategy. From Figure 6 and 7, we can also clearly see that the number of training epochs needed to achieved maximum accuracies can be much reduced whenever the fine-tuning strategy is applied to both pretrained models. Table 1 show the summary of the overall performance of VGG16, VGG19, ResNet50, ResNet101, and

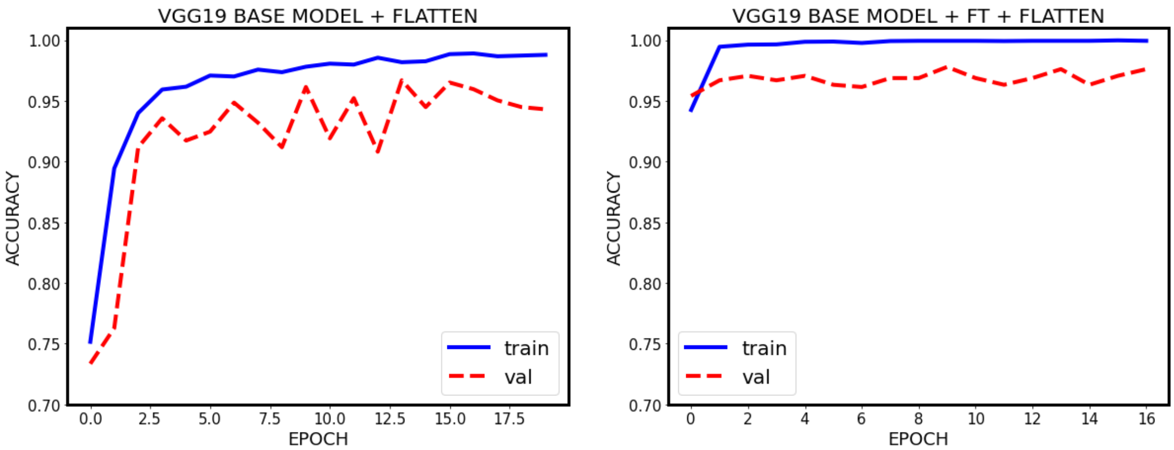

Figure 8. Performance of pretrained VGG19 model on multi-class MRI images before (left) and after (right) fine tuning

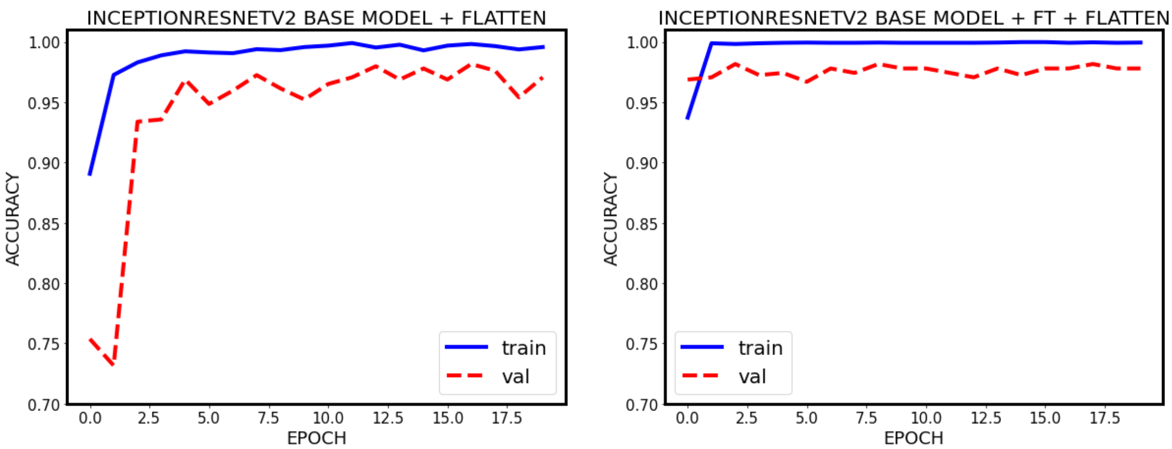

Figure 9. Performance of pretrained InceptionResNetV2 model on multi-class MRI images before (left) and after (right) fine tuning

Table 2. Performance summary of 5 pretrained CNN models on multi-class MRI images

PRETRAINED MODELS	*FLATTEN*		*FINE TUNED + FLATTEN*		*GAP*		*FINE TUNED + GAP*	
	VALID	*TEST*	*VALID*	*TEST*	*VALID*	*TEST*	*VALID*	*TEST*
VGG16	94.7	97.6	96.7	99.3	96.7	98.2	96.7	99.3
VGG19	95.0	98.3	98.0	99.4	96.5	98.4	97.5	99.4
RESNET50	94.5	97.8	97.5	99.5	97.5	99.1	98.7	99.3
RESNET101	97.5	99.1	97.4	99.3	97.4	98.6	96.7	99.1
INCEPTIONRESNETV2	96.0	99.3	97.6	99.3	97.7	99.7	97.9	99.4

InceptionResNetV2 models with four different configurations on BraTS 2019 dataset involving 2520, 280, 200 images for training, validation and testing respectively. From Table 1, it may also be observed that 99% testing accuracy score is obtained by two configurations namely VGG16 and InceptionResNetV2, each with fine tuning strategy and flatten layers. Meanwhile almost all of the models are capable of achieving more than 99% validation accuracies.

Figure 8 and 9 show the performance of the VGG19 and InceptionResNetV2 models on the training and validation MRI multi-class images. Although after fine tuning the accuracy scores are not significantly improved for all pretrained models however they are able to reduce considerably the number of epochs required to achieve the optimal output as is shown by VGG19 and InceptionResNetV2 pretrained models. Moreover we may also observe that the performance of both models is more robust after applying the fine-tuning strategy. From Table 2, which shows the summary of overall validation and testing accuracies of the pretrained models on MRI multi-class images, we found that all of the pretrained models with fine tuning strategy are capable of achieving more than 99.0% testing accuracy. Unlike on the binary image classification task, all the pretrained models on multi-class classification could be somewhat overfit as we found that the testing accuracy scores are always little higher that the validation accuracy scores.

4. Conclusion

It has been demonstrated that the pretrained deep CNN models are capable of achieving remarkable high classification accuracy scores on both MRI binary and multi-class images. The accuracy scores as high as 99.0% is obtained by applying fine-tuning strategy and feeding the high-level features maps extracted from the base model either into flatten layers or into global average pooling layers prior to classifying the images using fully connected layers. As the training, validation, and testing accuracies yield almost similar figures one to another, it may also be concluded that the models on MRI binary classification tasks are not overfit. On the other hand, we found that the pretrained CNN models with fine tuning strategy could be somewhat overfit on multi-class classification tasks as their testing accuracy scores a little bit higher than the validation accuracy scores. However, such an overfit may be easily overcome by changing the hyperparameters of the models such as learning rates and the optimizers employed.

In the very near future, we plan to further optimize the pretrained CNN models by optimally searching the best hyperparameters of the models such as number of convolutional layers at each block, type of activation functions, learning rates, and type of optimizers used.

Author contributions

Simeon Y. Prasetyo: Data curation, Training, validation, and testing the models, Writing-Original draft preparation.
Diaz D. Santika: Data curation, Conceptualization, Methodology, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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