Brain Tumor Classification Using Transfer Learning

by Naim Rochmawati

Submission date: 23-Mar-2023 11:55AM (UTC+0700)
Submission ID: 2044199532
File name: IEEE_Brain_Tumor_Classification_Using_Transfer_Learning.pdf (422.23K)
Word count: 3528
Character count: 17925

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1st Naim Rochmawati
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
naimrochmawati@unesa.ac.id

2nd Hanik Badriyah Hidayati
Department of Neurology Universitas Airlangga
Surabaya, Indonesia
hanikhidayati@fk.unair.ac.id

3rd Yuni Yamasari
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
yuniyamasari@unesa.ac.id

4th Wiyli Yustanti
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
wiyliyustanti@unesa.ac.id

5th I Made Suartana
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
madesuartana@unesa.ac.id

6th Agus Prihanto
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
agusprihanto@unesa.ac.id

7th Aditya Prapanca
Department of Informatics
Universitas Negeri Surabaya
Surabaya, Indonesia
adityaprapanca@unesa.ac.id

2022 Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE) | 978-1-6654-7581-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICVEE57061.2022.9930403

***Abstract*— One type of deadly disease is a brain tumor. To determine the presence of a brain tumor, it can be seen from an MRI image. In this research, we classified brain tumor MRI. The classification system uses transfer learning because only a few datasets are used. The Pre-Trained models used to extract features are VGG-16 and ResNet-50. Tests are carried out using several different parameters such as different batch sizes, optimizers, and learning rates. We evaluate the results using the confusion matrix. VGG-16 got the best accuracy of 0.96 using the Adam optimizer and ResNet-50 got the best accuracy of 0.94 using the RMSprop optimizer. From several different parameter variations, there is a relationship between parameter selection and accuracy results.**

***Keywords*— transfer learning, pre-trained model, Vgg-16, ResNet-50, brain tumor, optimizer, Adam, SGD, RMSProp**

I. Introduction

Humans live side by side with many diseases. One type of deadly disease is a brain tumor[1]. The brain is a vital organ that functions to move other body systems. It can be said, this organ is the center for regulating other body organs to work. If there is a disturbance or problem with the brain, it certainly affects on the performance of the body's organs as a whole.

Magnetic resonance imaging (MRI) is an imaging test that uses a magnetic field and radio waves to assess the inside of the body. This imaging examination is good for assessing soft tissues in the body, including the brain. So to find out whether the brain contains a tumor or normal can be seen from an MRI images.

Machine learning is a branch of artificial intelligence (AI) where the way it works is imitating the way humans learn without the need to be given explicit instructions. Examples of machine learning apparently exist in various forms that are very familiar with daily activities. Starting from transportation, technology, finance, education, health, and also social media. In short, it has been used for a lot of real-world applications[2]

One of the methods commonly used in machine learning is Convolutional Neural Network (CNN). Convolutional Neural Network or sometimes also called as ConvNet is part of a deep neural network, which is a type of artificial neural network that is generally used in image recognition and processing. This algorithm is specially designed for processing pixel data and visual images.

However, to find a model that has good accuracy and avoids overfitting, a large dataset is required. The more and more varied a dataset that is trained, it allows the resulting model to have better accuracy. The problem arises when the dataset used is small. One solution to overcome this is to use the transfer learning method.

Transfer learning is a method that has the basic principle of utilizing a previously trained model to be re-implemented in a new dataset where the existing dataset is not ideal enough to be trained from the beginning.

A pre-trained model is the use of pre-trained models which were trained on a large dataset by other people to solve our problem. There are many kinds of pre-trained models that have been published and are usually used as references in research, namely VGG, ResNet-50, Inception, Mobilenet, and many others. This study uses VGG-16 and ResNet-50.

In deep learning, to get good accuracy results, an optimization algorithm is needed or what is commonly called an optimizer. An optimizer is a function or algorithm that will modify NN attributes such as weight and learning rate so that it will improve the accuracy value. There are many kinds of optimizers. Three of them are Stochastic Gradient Descent (SGD), Adam, and Root Mean Square Propagation (RMSProp).

This study aims to classify brain tumors using a small dataset using the transfer learning method. The second goal is to explore the optimizer, learning rate, batch size, and epoch in the classification of brain tumor datasets to determine the relationship and their effect on the accuracy of results obtained.

A. Related Work

Several researchers have conducted research related to brain tumors. Brain tumor comparisons were carried out by Mehrotra et al using transfer learning methods AlexNet, SqueezeNet, ResNet-50, and GoogleNet. The best accuracy is obtained from Pre-Trained Alexnet with 99.4% accuracy with optimizer SGD and RMSProp[3]. Another study that compared the VGG-16, VGG-19, and Alexnet transfer learning methods has also been carried out with the best accuracy results being VGG-19[4]. Deepak et al. perform feature extraction using GoogleNet transfer learning with KNN and SVM classifiers[5].

In addition, there are also other methods used in classifying brain tumors using ensemble learning [13].

Research on brain tumor was developed by several researchers with various methods such as CNN-SVM [6], AlexNet [7], GoogleNet [8][9][10], VGGNet [11], ResNet-50 [12], In addition, there are also other methods used in classifying brain tumors using ensemble learning [13].

II. Research Method

This chapter describes the sequence of methods used in this research. This research has 6 steps, namely data retrieval, image preprocessing, Split dataset, Augmentation, comparing two methods of Pre-Trained VGG-16 and ResNet-50 models, Measurement. The sequence of steps can be seen in Fig..1.

The following is an explanation of each step in the diagram in Fig. 1:

A. Dataset

The dataset used in this study was taken from Kaggle[14]. The brain tumor MRI dataset consists of 253 images. these images are divided into two folders with the title yes and no. in the yes folder, there are 155 images consisting of brain images containing tumors and in the no folder, there are about 98 images where brain images do not contain tumors aka normal.

Some sample datasets of normal brain images without tumors can be seen in Fig. 2.

This dataset is a public dataset and can be downloaded from the Kaggle website.

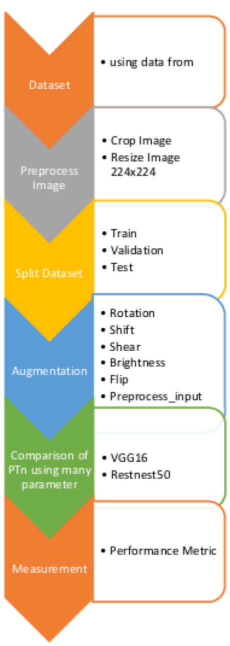


Fig.1. Research Method Diagram

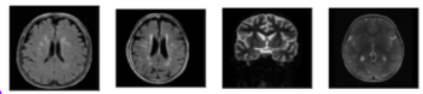


Fig. 2. Sample dataset of Brain MRI Images of NO

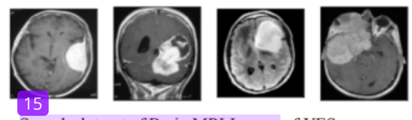


Fig. 3. Sample dataset of Brain MRI Images of YES

While the brain image dataset containing the tumor is shown in Fig. 3

B. PreProcessing

The preprocessing consists of two steps, cropping the image by looking for the left, right, top, and bottom points. Then the image will be cropped to the point where it is obtained.

Then the image is resized to 224x224. Because the transfer learning method used is VGG-16 and ResNet-50, the image size will be changed to 224x224.

Next, the dataset is divided into three parts, training, validation, and testing.

C. Augmentation

Because the dataset used is small, it is necessary to do augmentation before training. Augmentation is a technique of manipulating data by performing input operations of rotation, shift, shear, brightness, flip, and preprocessing.

This operation is done to avoid overfitting by making the data more varied. If the dataset is trained without augmentation first, the performance and accuracy will be worse than the dataset that has been augmented.

D. Comparison of Pre-Trained Models

Before discussing the comparison, we will first explain about Transfer learning.

1) Transfer Learning

Transfer learning is a technique that utilizes a pre-trained model to be used to classify new datasets so that there is no need to train data from the beginning. More details can be seen in Fig. 4.

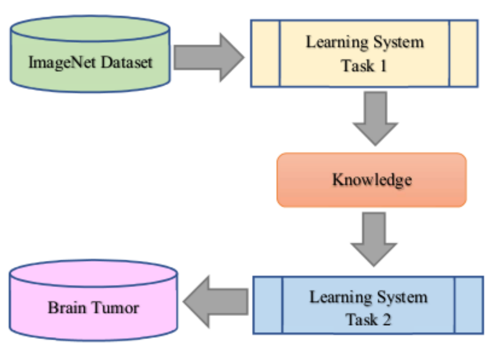


Fig. 4. Transfer Learning

There are two kinds of pre-trained that will be used:

a) VGG-16

VGG-16 is one of the CNN architectural models that won the ILSVR competition in 2014. VGG16 is a CNN model that utilizes a convolutional layer with a small convolutional filter specification (3×3). With the size of the convolutional filter, the depth of the neural network can be increased by more convolutional layers. As a result, the model is more accurate than previous CNN models.

The VGG16 model consists of 16 convolutional layers. The VGG-16 architectural model can be seen in Fig..5.

b) ResNet-50

ResNet-50 was first introduced by Kaiming et al in their paper entitled Deep Residual Learning for Image Recognition. ResNet-50 consists of 50 deep layers. ResNet-50 architectural model in Fig. 6.

Both VGG-16 and ResNet-50 images were obtained from a paper describing brain tumor classification using MRI images by Srinivas et. al[15].

2) Optimizer Adam, RMSProp, SGD

Deep learning is part of machine learning that is commonly used for various tasks, one of which is image classification. Deep learning will train the dataset using activation functions, hidden layers, loss functions, input, output, etc.

Modification of NN attributes such as weight and learning rate needs to be done so that the accuracy results can increase. The accuracy can be improved by using the optimizer algorithm. There are many kinds of optimizers. Three of them are SGD, Adam, and RMSProp

a) Stochastic gradient descent (SGD)

SGD is an optimization algorithm that is a variant of gradient descent. The way it works is iteratively reduces a loss function by moving in the direction opposite to that of the steepest ascent.

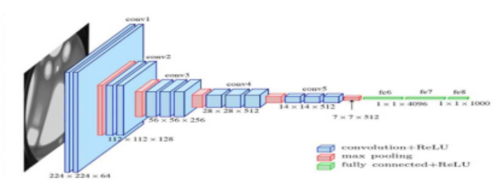


Fig. 5. VGG-16 architecture

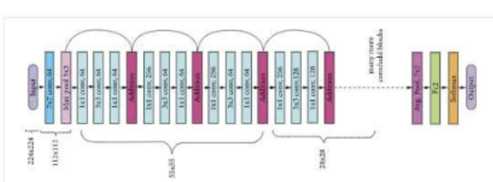


Fig. 6. ResNet-50 architecture

b) .Adam

Adam is actually a combination of the SGD optimizer and RMSprop. The way it works is that the learning rate for each weight will be adjusted according to the estimates of the first and second gradients. Therefore the term is called "adaptive moment estimation" or abbreviated as Adam.

c) Root Mean Square Propagation (RMSProp)

Basically RMSprop is a refinement of AdaGrad. although not published, but this optimizer is one of the most popular and well-known. RMSprop does not use the learning rate as a hyperparameter, but the learning rate used is adaptive where the learning rate changes over time..

3) Scenario of comparison

The comparison scenarios in this study are:

- Using VGG-16 with the Adam optimizer uses two different learning rates
- Using VGG-16 with three different optimizers
- Using ResNet-50 with three different optimizers
- Comparing the results of VGG-16 and ResNet-50 with three different optimizers
- Comparing the results of VGG-16 using the Adam optimizer and several different batch sizes.

E. Assessment

Prediction results from classification algorithms need to be measured whether the results obtained are good or not. How many predictions were correct and how many turned out to be wrong. In this study, measurements were made using performance metrics. In performance metrics, there are several terms known as a confusion matrix, precision, recall, and F1 Score. The confusion matrix is a 2x2 matrix that contains the actual and predicted values as shown in Fig. 7.

From the confusion matrix, several formulas can be derived, including:

a. Accuracy:
$$\frac{TP+TN}{TP+TN+FP+FN}$$
b. Sensitivity:
$$\frac{TP}{TP+FN}$$
c. Specificity
$$\frac{TN}{TN+FP}$$
d. Precision
$$\frac{TP}{TP+FP}$$
e. F1 score
$$2x\frac{recallxprecision}{recall+precision}$$

PREDICTION \ ACTUAL	Negative	Positive
Negative	TRUE NEGATIVE	FALSE NEGATIVE
Positive	FALSE POSITIVE	TRUE POSITIVE

Fig. 7. Confusion Matrix

Where TP stands for True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

III. Result and Discussion

After preprocessing by cropping and resizing the images, then dividing the data into training, validation and testing, the main process is to create a CNN model using Pre-trained VGG-16 and ResNet-50. The experiment result discussed below:

First, a comparison is made using Pre-Trained VGG-16 with batch size 32, epoch 20, and the Adam optimizer with two different learning rates, 0.0001 and 0.001. From Fig. 8, the resulting accuracy is higher when using a learning rate of 0.001.

The second test was carried out using Pre-Trained Model VGG-16 with batch size 8, epoch 10, and three different optimizers, SGD, Adam, and RMSProp parameters. All use the same learning rate of 0.0001. The experimental results can be seen in Fig. 9.

The best accuracy value is generated by using the Adam optimizer. This is not to say that Adam's optimizer is always better than the other two. It could be that when using a different learning rate, another optimizer is better. Need more experiments to find out.

The third experiment was carried out using the pre-trained ResNet-50 model with batch size 8, epoch 10. This experiment used three different optimizers and the learning rate was the same, 0.0001.

The experimental results can be seen in Fig. 10. The best accuracy is obtained from the RMSProp optimizer, which is 0.94 which turns out to be different from the previous study in Fig. 9, where VGG-16 obtained the best results when using the Adam optimizer.

When the results of the second and third experiments are compared, in Fig. 11, as previously explained, the best accuracy results are obtained by VGG-16 when using the Adam optimizer of 0.96 and ResNet-50 using RMSPro with an accuracy of 0.94.

The last experiment used the Pre-Trained VGG-16 model by using a combination of different batch sizes and epochs. The optimizer used in this last test uses the Adam optimizer with a learning rate of 0.0001. The test results can be seen in Fig. 12.

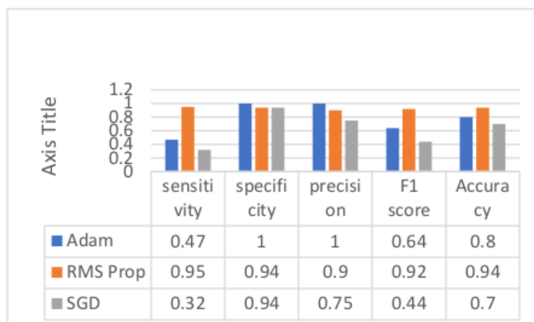
By using pre-trained VGG-16, the highest accuracy results when using batch size 8 and epoch 10 are 0.96. while the smallest value of accuracy is obtained when using batch size 32 and epoch 20. When Fig. 9 and Fig. 12 are compared, VGG-16 when using the Adam optimizer and a learning rate of 0.0001 the results may differ due to the difference in the selected batch

	sensitivity	specificity	precision	F1 score	Accuracy
lr 0.001	0.95	0.94	0.9	0.92	0.94
lr 0.0001	0.79	0.97	0.94	0.86	0.9

Figure 8. VGG-16 using Adam optimizer with different learning rate

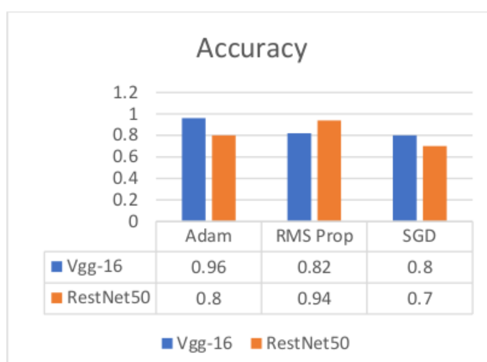
	sensitivity	specificity	precision	F1 score	Accuracy
Adam	0.95	0.97	0.95	0.95	0.96
RMS Prop	0.63	0.94	0.86	0.73	0.82
SGD	0.68	0.87	0.76	0.72	0.8

Figure 9. VGG-16 using different optimizers



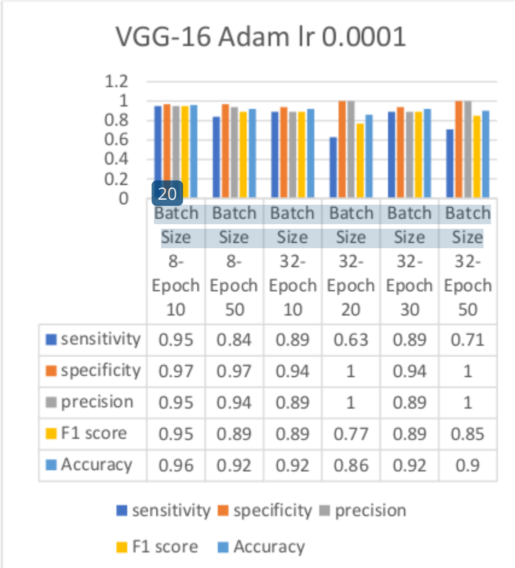
	sensitivity	specificity	precision	F1 score	Accuracy
Adam	0.47	1	1	0.64	0.8
RMS Prop	0.95	0.94	0.9	0.92	0.94
SGD	0.32	0.94	0.75	0.44	0.7

Figure 10. ResNet-50 using different optimizers



	Adam	RMS Prop	SGD
Vgg-16	0.96	0.82	0.8
RestNet50	0.8	0.94	0.7

Figure 11. VGG-16 vs ResNet-50 using different optimizers



	Batch Size 8-Epoch 10	Batch Size 8-Epoch 50	Batch Size 32-Epoch 10	Batch Size 32-Epoch 20	Batch Size 32-Epoch 30	Batch Size 32-Epoch 50
sensitivity	0.95	0.84	0.89	0.63	0.89	0.71
specificity	0.97	0.97	0.94	1	0.94	1
precision	0.95	0.94	0.89	1	0.89	1
F1 score	0.95	0.89	0.89	0.77	0.89	0.85
Accuracy	0.96	0.92	0.92	0.86	0.92	0.9

Figure 12. VGG-16 using different batch sizes and epochs

size. in Fig. 9. When using batch size 32, the accuracy is 0.94 while when using batch size 8 in Fig. 12, the accuracy is 0.96.

IV. Conclusion and Future Work

Brain tumor classification experiments conducted with a small dataset of only 253 images turned out to be completed using the Transfer learning method. The Pre-Trained models used to extract features are VGG-16 and ResNet-50. By using several different parameters such as different batch size, optimizer, and learning speed, the result is that VGG-16 gets the best accuracy of 0.96 using the Adam optimizer and ResNet-50 gets the best accuracy of 0.94 using the RMSprop optimizer.

From the many comparison experiments carried out, there is a strong relationship between parameter selection and the accuracy of results obtained. Choosing the right batch size, epoch, optimizer, and learning rate will produce good accuracy results. On the other hand, if the selected parameters do not fit, the results are not very good.

For future research, it is necessary to do research on how to select hyperparameters automatically for transfer learning because searching is expensive and takes time and effort.

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