

## Original Research Article

# Classification and Segmentation of Brain Tumor Using EfficientNetB7 and UNet

### ABSTRACT

Tumors are caused by uncontrolled growth of abnormal cells. Magnetic Resonance Imaging (MRI) is modality that is widely used to produce highly detailed brain images. In addition, a surgical biopsy of the suspected tissue (tumor) is required to obtain more information about the type of tumor. Biopsy takes 10 to 15 days for laboratory testing. Based on a study conducted by Brady in 2016, errors in radiology practice are common, with an estimated daily error rate of 3-5%. Therefore, using the application of artificial intelligence, is expected to simplify and improve the accuracy of doctor's diagnose.

**Keywords:** Convolutional neural network; U-Net; EfficientNetB7; Machine learning; Brain tumor

### I Introduction

Brain tumors are solid neoplasms within the skull. These tumors are caused by uncontrolled growth of abnormal cells. Classification of brain tumors is divided based on the location of the tumor, the type of tissue produced, and whether the tumor is malignant (malignant) or benign (benign) and several other considerations [1]. Magnetic Resonance Imaging (MRI) is modality that is widely used to produce highly detailed brain images. In addition, a surgical biopsy of the suspected tissue (tumor) is required to obtain more information about the type of tumor [2]. To diagnose brain tumors, doctors usually perform a biopsy and direct observation through the brain images that have been obtained. Biopsy requires a slow time of around 10 to 15 days for laboratory testing, whereas manual diagnosis carries a risk of error [3]. Based on a study conducted by Brady in 2016, errors and discrepancies in radiology practice are common, with an estimated daily error rate of 3-5%. So we need an alternative method that is fast and has

a low error rate to help doctors make decisions [4].

Machine learning, the cornerstone of today's artificial intelligence (AI) revolution, is bringing a new method to clinical practice with medical images. For example, for diagnosing various conditions from medical images, machine learning has been shown to have performance on par with medical experts [5]. In practice, machine learning usually begins with a learning algorithm system by calculating the features or image augmentations used to make predictions or accurate diagnoses [6].

Transfer learning is an approach in machine learning that leverages the knowledge gained from training on one task to help solve a different task. In this paper, we use EfficientNetB7 to classify and UNet to segmented the brain tumor. The results of the journal produce an architecture new one named EfficientNet where EfficientNet-B7 has results better accuracy or on par with other networks but by size and floating point operations per second (FLOPS) smaller one. UNet is an architecture in convolutional neural network (CNN) for medical segmentation.

Based on the description above, with the advantages of machine learning algorithms, especially the CNN method in classifying brain tumors and contour detection, a study was conducted on the performance of machine learning on MRI image results for patients with brain tumors using transfer learning EfficientNetB7 and UNet.

## **II Convolutional Neural Network (CNN)**

The Convolutional Neural Network (CNN) is a type of Deep Neural Network that is an advancement of the multilayer perceptron (MLP) and is specifically designed to process two-dimensional data. CNN is primarily used for image data due to its high network depth and effectiveness. MLP is not ideal for image classification because it

does not retain spatial information from image data and treats each pixel as an independent feature, resulting in unfavorable outcomes [7].

CNN is famous these days for image recognition and image related prediction, which borrows the concept of convolution from classical linear system screening, where 2D. Therefore, the concept of convolution is naturally combined into a neural network (NN) to develop what is called a CNN [8].

CNN performs the convolution process by moving a convolution kernel or a filter of a certain size to an image, the computer gets new representative information from the multiplication of the part of the image with the filter used. From the results of the convolution, smaller and overlapping image fragments will be produced. Each thumbnail of the convolution results is then used as input to produce a feature representation. This gives CNN the ability to recognize an object, regardless of where the object appears in an image. The images will then be stored in an array and downsampled. Downsampling is done to reduce the size of the array so that the computation is done lighter. Downsampling is divided into two, namely max pooling and average pooling. Max pooling takes the largest pixel size in each convolution kernel layer while average pooling takes the average pixel size of each convolution kernel.

CNN has three types of layers: Convolution, pooling, and fully connected layer. The convolution layer is made up of multiple convolution kernels which learn feature representations from the input and generate feature maps. feature maps are the first result of convolution of the input with the learned kernel, and then, by applying to the convolution result and non-linear activation function.

### **III Transfer Learning EfficientNet**

Transfer learning is a machine learning method in which a model is developed for a task that is reused as a starting point for modeling in a second task. There are many

types of transfer learning that can be implemented in an ML model. Selection of the type of transfer learning according to the use or needs of the desired task [9]. In this study, transfer learning is used, namely EfficientNet.

EfficientNet, first introduced by Tan and Le in 2019 is one of the most efficient models that achieve state-of-the-art accuracy on imagenet and general image classification transfer learning [10],[11]. EfficientNet is a collection of models built from base models developed through a search for neural network architectures. EfficientNet's performance is better than all its predecessors with the same computation and memory requiring a large margin [12].

#### **IV UNet Architecture**

U-Net is one of the usual types of CNN used for semantic image segmentation [13]. U-Net consists of the downsampler and upsampler. on layers downsampler, there are two 3x3 unpadded convolutions, which will then go through the ReLU activation function and a 2x2 layer maxpool with stride 2. On each stage of downsampling will occur doubling feature. On the upsampler layer, there is an upsampling process followed by a 2x2 convolution layer which will split the number of features in half, process feature pooling, two 3x3 convolution layers, each with a ReLU activation function. Layers finally in the form of 1x1 transposition convolution layer which used to transform the 64 component feature vectors into 3 classes [14].

#### **V Materials and Methods**

Research on the classification and contour detection of brain tumors on MRI imaging results using machine learning algorithms was conducted at the Biophysics and Medical Physics Laboratory of the Physics Study Program at Udayana University with data taken from Kaggle containing 7022 brain tumor images with brain tumor classifications glioma, meningioma, no tumor brain and pituitary [15]. This data

contains data taken from the Plos One journal entitled "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition" by Jun Cheng, et al from the school of Biomedical Engineering Southern Medical University, Guangzhou, China [16],[17]. To evaluate the brain tumor classification model, data obtained from The Cancer Imaging Archive under the auspices of the University of Arkansas for Medical Science under contract from the National Cancer Institute (NCI) were used. Meanwhile, the dataset for detecting brain tumor segmentation was obtained from The Cancer Genomic Atlas (TCGA) [18].

This research was conducted using the Python programming language in the Google Colaboratory code editor. Modeling in this study uses several libraries as modules that contain a set of code that can be used repeatedly in different programs. After importing the model supporting library in this study, data preprocessing was carried out. Data preprocessing is the process of entering or combining data into the dataset model to be created. The dataset was obtained from Kaggle which contains 7022 MRI images with the classification of brain tumor images of glioma, meningioma, pituitary and no tumor. For segmentation detection of brain tumors using the UNet architecture, the dataset used was obtained from The Cancer Genome Atlas (TCGA) with images taken from 110 patients. At the data preprocessing stage, the data is divided into training and testing. After preprocessing the data, the process of making a machine learning model is carried out. At this stage, hyperparameters are determined according to the existing data and problems. After making the model is complete, the model training process is carried out to improve the model's ability to classify brain tumor image data according to the label that has been given. The next process is to evaluate the results of model training. If the model accuracy can still be improved, it can be

improved by optimizing the hyperparameters used in machine learning modeling. The research procedure is shown in Figure 1.

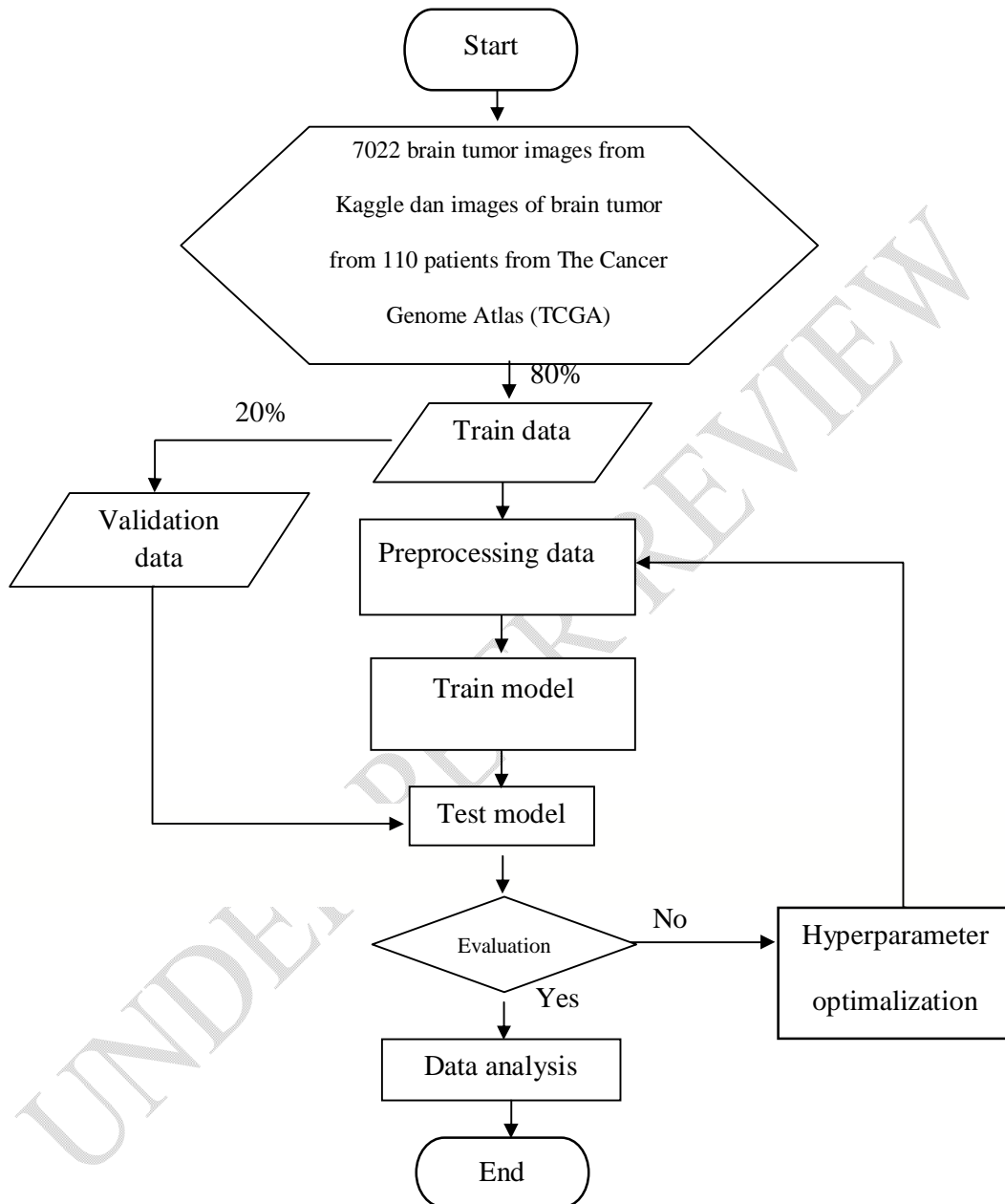


Figure 1 Research procedure

## VI Result

### *Model Architecture*

The CNN model shown consists of a base model that uses EfficientNetB7 transfer learning. EfficientNetB7 has the same performance well with limited computing needs. This transfer learning has 66 million parameters for classifying and analyzing images. The model consists of 3 layers, with the first layer consisting of the Convolution2D layer, the Convolution2D layer is used for data in the form of images, this function is to recognize images based on the pixels contained in the image, using the Relu activation function. At this stage, 16 filter parameters are loaded, meaning that the number of filters issued in the convolution process is 16 with a size of 3x3 (kernel\_size = (3, 3)). For the 2nd layer, 32 filter parameter are loaded. For 3<sup>rd</sup> layer, 64 layer are loaded and for 4<sup>th</sup> layer, 128 filter layer are loaded. Then input\_shape for all layer are (150, 150, 3) this means that all image sizes that enter the input layer are 150x150 pixels in size and 3 color layers in matrix form. The activation used for all layer are the Rectifier Linear Unit (ReLU) because this function is a function commonly used for CNN. Furthermore, the MaxPooling2D layer is added which is used to reduce the image resolution while maintaining the information in the image, the way the MaxPooling2D layer works is to take the maximum value from the processed data. Where the pooling size on the first layer is 2x2. Thus, the analysis will be faster due to the small size of the feature maps.

Then do the flatten. With this command, all matrices become a single vector size which will be used as input for the neural network in the future. The next step is to give dense or add a hidden layer. The first hidden layer is 1024 in size, which means that there are 1024 neurons in this layer. Then the next parameter is activation='relu'. Next is used hidden layer 512. Dropout is used to reduce overfitting in the model. Then next is

the definition of the output layer. Because the data type is categorical (glioma, meningioma, pituitary, and no tumor) there are 4 neurons according to the number of labels in the dataset.

The UNet architecture in the model for detecting brain tumor contours uses 10 convolution layers. In layer 1 Conv2D with 64 filters and a kernel size of  $3 \times 3$  is used to convolve the input image with the output being a feature map with a smaller size. The activation layer used is ReLU, which functions to provide non-linearity to feature maps which are the output of the previous layer. BatchNormalization is a batch normalization layer on the 3rd channel (RGB). This layer functions to speed up training and model stabilization by normalizing each batch of data that is input to the layer. Activation is an activation layer with the ReLU activation function. This layer is used to provide non-linearity to the normalization results generated by the BatchNormalization layer. MaxPooling2D is a pooling layer with a pool size of  $2 \times 2$ . This layer serves to reduce the spatial dimension of the feature map so that the information retrieved becomes more focused and not too much. For layer 2 Conv2D uses 128 filters and a kernel size of  $3 \times 3$ . With BatchNormalization, the same activation and Maxpooling2D functions as layer 1 to layer 9. Layer 3 uses Conv2D with 256 filters and the same kernel size as the other layers. Layer 4 uses 512 Conv2D filters with the same kernel size as the previous layer. On layer 5 use 1024 Conv2D filters with the same size as the previous layer. In layer 6, the concatenate layer is used which is a layer combining feature maps from two layers, namely the Conv2DTranspose layer and the Conv4 layer. This layer functions to combine the upsampled feature map with the feature map on a lower layer horizontally, thereby adding spatial information and enriching the features used for segmentation. In addition, the Conv2DTranspose layer is also used which is a convolution transpose layer with 512 filters and a kernel size of  $2 \times 2$  and a stride of  $2 \times 2$ . This layer functions to

carry out convolution transpose operations (upsampling) on the feature map produced by the previous layer so as to produce a larger feature map. Layer 6 also uses a Conv2D layer with a total of 512 filters with a kernel size of  $3 \times 3$ . Layer 7 just like layer 6 also uses Conv2DTranspose and a concatenate layer. At layer 7, it uses 256 filters with the same kernel size as the other layers. Layer 8 uses 128 filters with the same kernel size as the other layers, layer 8 also uses Conv2D Transpose and concatenate layers with the same parameters as layers 6 and 7. Layer 9 uses 64 filters with the same kernel size as the other kernels. Layer 9 also uses the Conv2D and concatenate layers. Layer 10 uses 1 filter with a kernel size of  $1 \times 1$ . Layer 10 uses sigmoid activation which is used to determine the probability of an input data being included in the target class or not.

### Confussion matrix

Figure 2 is the result of multiclass accuracy. The figure shows the number of comparison results from machine learning algorithm predictions with actual results (ground truth). From these images obtained 1291 true positive data for Glioma, 1148 true positive data for meningioma, 1550 true positive data for no tumor and 1446 true positive data for the pituitary.

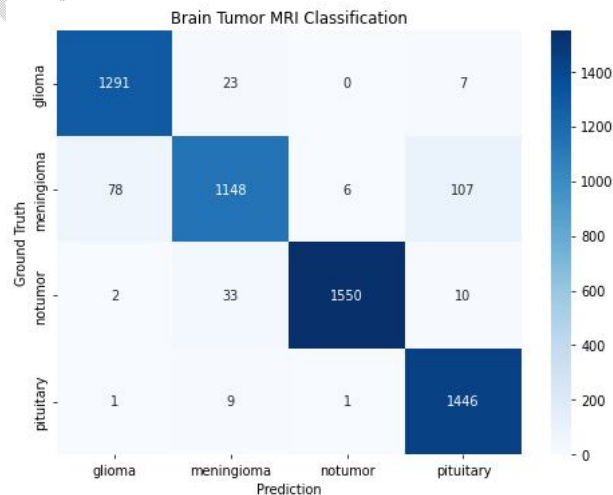


Figure 2. Confussion matrix result

### *Accuracy, Sensitivity, Precision and specificity*

Table 1. Table of results for accuracy, sensitivity/recall, precision, specificity

	<b>Presisi</b>	<b>Sensitivitas/recall</b>	<b>Specificity</b>
<b>Glioma</b>	0.94	0.98	0.99
<b>Meningioma</b>	0.95	0.86	0.98
<b>No Tumor</b>	0.99	0.97	1.00
<b>Pituitari</b>	0.92	0.99	0.97
<b>Accuracy</b>			0.95

The results for glioma labeling have a precision value of 0.94, a sensitivity of 0.98 and a specificity of 0.99. For meningioma labels obtained a precision value of 0.95, a sensitivity value of 0.86 and a specificity of 0.98. If there is no tumor label, the precision value is 0.99, the sensitivity is 0.97 and the specificity is 1.00. For the pituitary label, a precision value of 0.92 was obtained, a sensitivity of 0.99 and a specificity of 0.97. With a total overall accuracy of 0.95.

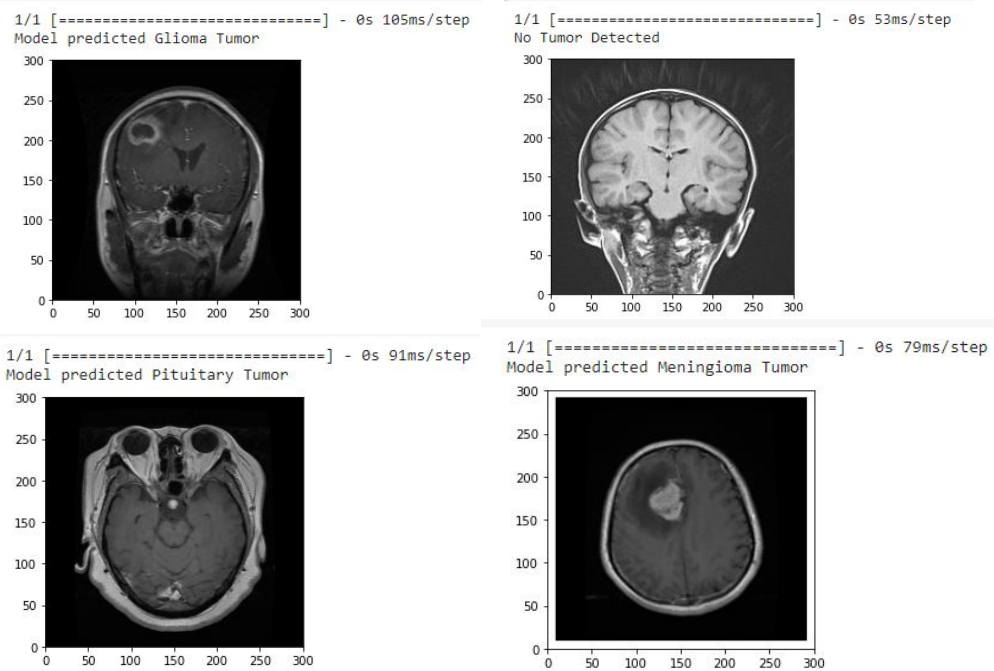


Figure 3. Result of Predicted Tumor

The output of brain tumor classification is shown in Figure 3. The classification of brain tumors defined in this model were glioma, meningioma, pituitary brain tumor and no tumor was detected. The results of the prediction of the MRI image are in the form of an image measuring 150×150 with 3 RGB color channels. The results of this classification prediction obtained an overall accuracy of 95%.

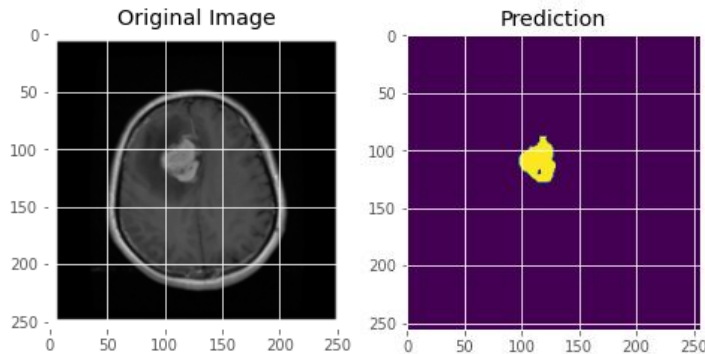


Figure 4. Result of Brain Segmentation

In Figure 4, the model predicted results of the tumor segmentation portion in the original image. The value of Intersection over Union (IoU) is 0.99. Intersection over union or also known as the Jaccard index is an evaluation metric used to measure how much the segmentation or detection object produced by a model matches the actual object in the image. This metric measures the overlap between two areas, namely the prediction area (the result of segmentation or detection from the model) and the reference area (the actual object that is expected to appear in the image). IoU is calculated by dividing the overlapping area by the combined area of the two areas.

## V Conclusion

The objective of this study is to improve the accuracy of brain tumor diagnosis and segmentation, with the aim of aiding physicians in identifying specific brain tumors. By implementing transfer learning with the EfficientNetB7 model for brain tumor classification, we achieved an accuracy of 95%. For brain tumor segmentation

using the UNet architecture, we achieved an Intersection over Union value of 99%. The use of EfficientNetB7 and UNet for brain tumor classification and segmentation, respectively, can effectively improve brain tumor diagnosis.

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