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Brain Tumor Classification for MR Images Using Transfer Learning and EfficientNetB3

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Abstract

Brain tumors are one of the diseases that take many lives in the world, moreover, brain tumors have various types. In the medical world, it has an technology called Magnetic Resonance Imaging (MRI) which functions to see the inside of the human body using a magnetic field. CNN is designed to determine features adaptively using backpropagation by applying layers such as convolutional layers, and pooling layers. This study aims to optimize and increase the accuracy of the classification of brain tumor MRI images using the Convolutional Neural Network (CNN) EfficientNet model. The proposed system consists of two main steps. First, preprocessing images using various methods then classifying images that have been preprocessed using CNN. This study used 3064 images containing three types of brain tumors (gliomata, meningiomas, and pituitary). This study resulted in an accuracy of 98.00%, a precision of 96.00%, and an average recall of 97.00% using the model that the researcher applied.

Keywords: *Brain Tumor Classification, Convolutional Neural Network, EfficientNet, Transfer learning.*

1. Introduction

Health is one of the important factors in supporting human life activities. In carrying out daily activities, humans often interact with various objects that can cause the emergence of disease, and the incidence of disease in humans gradually grows throughout the world. Diseases of the internal organs are more acute compared to diseases of the external organs such as diseases of the brain [1], [2] .In human physiology, the brain is one of the vital internal organs and also a major part of the Central Nervous System (CNS) and also abnormalities / diseases in the brain are one of the main medical emergencies. The brain is also a highly metabolically active organ, which takes up about one-fifth of the body's total oxygen consumption [3]. As a result, the oxidative metabolism of the brain produces the continuous production of a large number of Reactive Oxygen Species (ROS), most of which are produced by mitochondria. While ROS is needed to perform normal cognitive functions, they are mostly produced by activated microglia and astrocytes.

Accurate and precise classification of MR images of brain tumors plays an important role in clinical diagnosis and decision-making for patients [4]. Magnetic resonance imaging (MRI) is a type of scanning that uses a strong magnetic field and radio waves to produce detailed images of the inside of the body. The MRI scanner includes a large tube containing a strong magnet. MRI is an established imaging technique in various fields of medicine that has become fundamental for the non-invasive diagnosis of soft tissue diseases because it has the advantage of not using ionizing radiation, avoiding the biological damage associated with other three-dimensional imaging techniques such as CT and CBCT [5], [6]. MRI creates images using magnetic fields and strong radio static and some frequency signals. When placed in a magnetic field, all substances are magnetized into degrees that depend on the degree of their magnetic protility. Unfortunately, the field-strength magnetic variations that occur at the interface between the dental material and adjacent can make spatial distortion and signal loss, resulting in the artifacts in figure [7].

Efficientnet is one of the scaling methods in the Convolution Neural Network (CNN) published by google at the end of 2019. Convolutional Neural Network (CNN) is one of the most widely used methods. [8] Can be systematically improved based on available resources, and the model can achieve better accuracy than traditional convNets [9]. This method not only fixated on accuracy, but also emphasizes efficiency in its processing. This method scales the

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model to work faster with fewer parameters used than previous SOTA models. EfficientNet uses three types of scaling, namely Depth Scaling, Width Scaling and Resolution Scaling.

In a study conducted by Sunada et al. (2019) on the classification of brain tumors using the CNN method [10]. Researchers developed a CNN model to classify brain tumors in contrast T1-Weighted enchanted MRI images. The created system consists of two significant steps. First, image preprocessing uses some image processing techniques and then classifies preprocessed images using CNN. The results of this study indicate the level of accuracy achieved is 93.33%.

In a study conducted by Rehman et al. (2020) regarding the classification of brain tumors using the K-means clustering method and deep learning with synthetic data augmentation [11]. Researchers segmented and classified brain tumors using K-means clustering and deep learning methods with a dataset in the form of a four-stage synthetic augmentation system to classify brain tumors. The results of the study found that the resulting level of accuracy was higher, reaching 94.06%.

In a study conducted by Zhao et al. (2019) regarding the classification of brain tumor MRI images using transfer learning and fine-tuning methods [4]. Researchers took a different process approach, namely separating the k-nearest-neighbours, Support Vector Machines, Boosted Trees, Decision Trees, and Random Forest methods at the preprocessing stage. The results of the research conducted found that the level of accuracy produced was higher than in previous studies, namely 94.82%.

In a study conducted by Nayak et al. (2022) regarding the classification of brain tumors using the Dense EfficientNet method [12]. This research uses a method of adding layers that can be said to be fully connected with the basic EfficientNet-B0 model. The results of the research conducted found that the resulting accuracy rate reached 98.78%.

Meanwhile, in a study conducted by Abiwinanda et al. (2019) regarding the classification of MRI images using the CNN hyper-parameter optimization method [13]. With this deep learning approach, researchers get an accuracy of 84.19%.

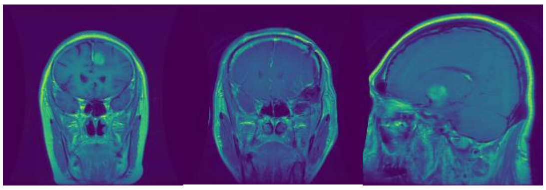
In this study, researchers used one of the transfer learning methods because this method is still better than other methods because the transfer learning method processes images that have been pre-trained beforehand [14]. This allows the processed images to be faster and more efficient during the next image training process. And also the purpose of this study is to compare the results of the classification of brain tumors with different methods [11].

Based on the background explanation above, the researcher aims to conduct research by applying the EfficientNet-B3 CNN model as an MRI classification of brain tumor images using the same dataset with a satisfactory accuracy result of 98.00%.

2. Research Methods

2.1 Dataset

In this study, researchers used the CE-MRI dataset availablein(https://figshare.com/articles/dataset/brain_tumor_dataset/1512427). This dataset has a total of 3064 images. Data were collected from 233 patients with three types of brain tumors namely: meningioma, glioma, and pituitary tumor with sample images shown in figure 1 and the number of each image listed in table 1 with an image size of 512 x 512 pixels, and a pixel size of 49mm x 49mm. This dataset is in MATLAB format (.mat file).



(a) (b) (c)

Figure 1. (a) Meningioma. (b) Glioma. (c) Pituilary

Table 1.Table dataset

Tumor	Patients	MRI
Meningioma	82	708
Glioma	89	1426
Pituitary	62	930
Total	233	3064

2.2. Images Preprocessing

The images obtained can be said to be unclear, therefore, these images need to be normalized before further processing [12], [15]. CE-MRI data are 2-D images measuring 512 x 512. There is a misbalancing of data in the dataset which can be seen in table 1, so the researcher balances the data on the dataset used. Researchers carried out random undersampling of data for all classes in the dataset which aims to reduce random training data for each class, as can be seen in table 2. All classes are limited to a maximum of 647 data in each class. In this study, researchers fed MRI images directly into CNN and a convolutional kernel was applied to the pixel intensity in the MRI images [16[1]–[25]]. However, the intensity values in the MRI images do not have a fixed value, and it has been observed that the intensity values across the MRI images vary greatly among subjects.

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Table 2. Balancing Data Results

Tumor	MRI
Meningioma	647
Glioma	647
Pituitary	647
Total	1941

2.3. CNN model EfficientNet

To classify various types of tumors, researchers used the CNN fine-turned EfficientNet-B3 method [17]. The researcher balances the dimensions of the image using a method that includes: width, depth, and resolution, which are part of the efficientNet scaling process, which is useful for increasing the accuracy and efficiency of the process.

EfficientNet consists of eight sections, namely B1, B2, B3 to B7. Researchers use the basic efficientNet-B3 method because it has higher accuracy compared to several other models. EfficientNet uses the following equation:

$$\begin{aligned} Depth &: d = \alpha^{\phi} \\ Width &: w = \beta^{\phi} \\ Resolution &: r = \gamma^{\phi} \\ \alpha \geq 1, &\beta \geq 1, \gamma \geq 1 \end{aligned} \tag{1}$$

where α, β, γ are constants that can be specified with a small network search. Intuitively φ is a user-defined coefficient that controls how many more resources are available for model scaling, while α, β, γ determine how to assign the rest of the previous process to the depth, width, and resolution specifications [18]. Since the optimal d,w,r depends on each other and the values will change depending on different conditions, conventional methods mostly scale ConvNets in one of these dimensions:

Depth (d): Scaling network depth is the most common way many ConvNets[19], [20]. On deeper reasoning, ConvNet can capture richer and more complex features, and generalize well to new tasks. However, deeper tissues are also harder to train due to missing gradients

Width (w): Scales the width typically used on small-sized models [21]. A wider network tends to be able to capture features that are smoother and easier to train. However, very extensive but shallow networks tend to have difficulty in capturing higher-level features.

Resolution (r): With higher-resolution input images, ConvNets has the potential to capture smoother patterns. Starting at 224x224 in early ConvNet, modern Con vNets tend to use 299x299 for better accuracy [22]. GPip (Huang et al. 2018) achieved the highest imageNet accuracy with a resolution of 480x480. Higher resolutions, such as 600x600 are also widely used in ConvNets object detection.

Attention layers are illustrated in Figure 2. This can be applied to any feature map in the CNN model [23]. It is assumed that the input size of the feature map is NxNxC, where NxN is the size of the 2D map and C is the number of channels. The attention module starts by pressing the feature map using two convolutional layers in a row so that the size becomes NxNx16. Then use the locallyConneced2D layer followed by the activation sigmoid function to learn the NxN weights. Then another convolutional layer is used to replicate weights across time dimension C. It is important to note here that this layer is followed by a linear activation function, which means weights can take various values. However, after averaging a feature map with attention into a single vector feature of length C, researchers scaled the results through division by vector mean weight. The researcher adds an attention layer at the top of the model, we delete the last two layers in Figure 3, and replace them with the attention module illustrated in Figure 2.

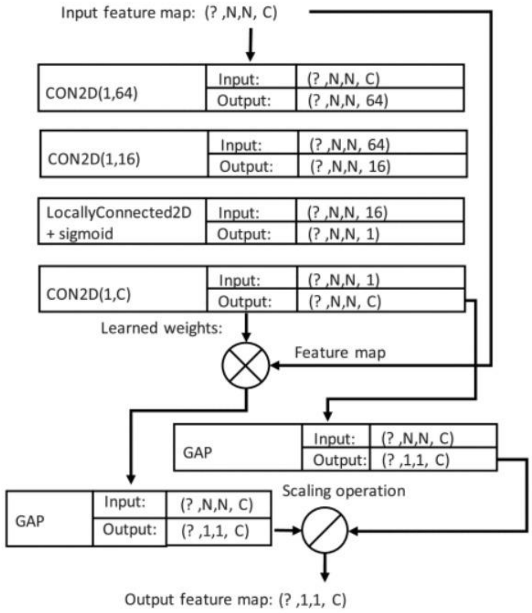

Figure 2. *Attention layers* [21]

2.4 Transfer Learning

Transfer learning is a machine learning technique in which the knowledge gained during training in a problem is used for training in another task or field [24], [25]. In deep learning, the first few layers are trained to define the characteristics of the image. During the Transfer Learning process, the last few layers of the trained network can be removed and retrained with a new layer on an image that you want to train. This Transfer Learning approach using previously trained network knowledge with large amounts of visual data in the new task is very advantageous in terms of saving time and achieving high accuracy compared to training a model from scratch.

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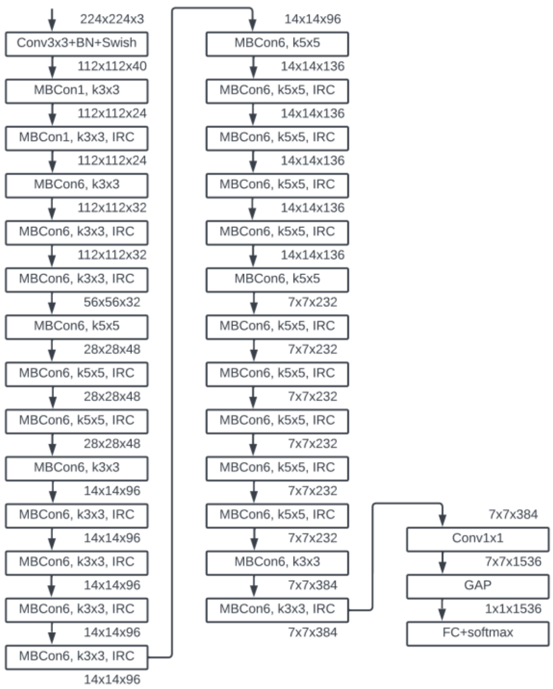

Figure 3. *Architecture EfficientNet* [21]

2.5 Metrix Performance

Researchers have evaluated performance-based image-based classifications on recall, precision, f1-score, and accuracy. Sensitivity, also called recall, is a True Positive (TP) ratio that is actually correctly classified based on a diagnosis test using formulas (2), (3), (4). This illustrates how well the classifier is at classifying the correct type of tumor. Specificity is the correct True Negative (TN) ratio of the diagnostic test and shows how well the classifier is at predicting negative conditions. Precision is the positive predictive level (PP). The F1-score measures classification performance in terms of recall and precision. Accuracy is the accuracy of the overall classification of TP and TN.

$$Presisi = \frac{True\ positive}{True\ prositive + False\ positive} \quad (2)$$

$$Recall = \frac{True\ positive}{True\ prositive + False\ negative} \quad (3)$$

$$F1 - score = 2x\ \frac{Presisi\ x\ Recall}{Presisi + Rexall} \quad (4)$$

3. Result and Discissions

To test the performance of the proposed approach, researchers adopted the same experimental as in (Khan et al. 2021), and randomly divided the CE-MRI data into three classes of approximately the same size of each class. Researchers confirmed that no images appeared in equality in the training and testing sets.

3.1. Training and Optimizing parameters

Training in terms of blocks in each CNN takes about 20-30 minutes, concretely, it depends on the choice of training parameters and fine-tuning, proper convergence, accuracy of training validation, and errors. Training will stop automatically if there is no improvement with respect to validation accuracy and errors. Researchers used trial-and-error-based to determine these values and conducted experiments with different values from these parameters. During the training process, we found that the exact convergence depends on the α learning rate, the α_b learning rate of each layer and the scheduling rate ϒ. The optimal values for α = 0.01 and α_b = 0.10 ensure proper convergence. If researchers set α and α_b very large, then CNN fails to meet properly and results in low performance on test and validation data. If we set the α and α_b very small, then the convergence process slows down. The value of ϒ is related to the speed of convergence. If convergence is very slow, then ϒ must be large enough to keep the learning rate high. If convergence is very fast, then ϒ should be small enough to reduce learning rates and prevent tissues from overfitting.

Researchers set the base-learning rate of each layer to be twice as high as α_b, the mini batch size for training at 64 (the maximum mini batch size supported by the researcher's GPU for EfficientNet). Researchers validate the training process after each epoch and stop the training process automatically if there is no improvement in the validation test for 15 epochs.

3.2. Evaluation Graph

The evaluation graph is shown in figure 4 which shows the trend of training data and data validation and obtained balanced results and this is one of the benchmarks that the results of accuracy will be high because the data to be trained is really balanced. In training and validation loss, the best epoch is obtained in the 40th iteration of the epoch. While training and validation accuracy, the best epoch is obtained in the 8th iteration of the epoch. In training and validation loss, it can be seen if the graph does not show any underfitting or overfitting. Meanwhile, in the training and validation accuracy graphs, there is a slight overfitting of data. The results of identifying the three classes (pituitary tumors) produce better accuracy than other classes where the other classes are not mixed. Table 4 shows the results of performance measurements in a model. This shows the precision, recall, F1-score and supports that the author has evaluated. In this model, 89%, 99%, and 100% precision was obtained for class 1 (meningioma), class 2 (pituitary), and class 3 (gliomata).

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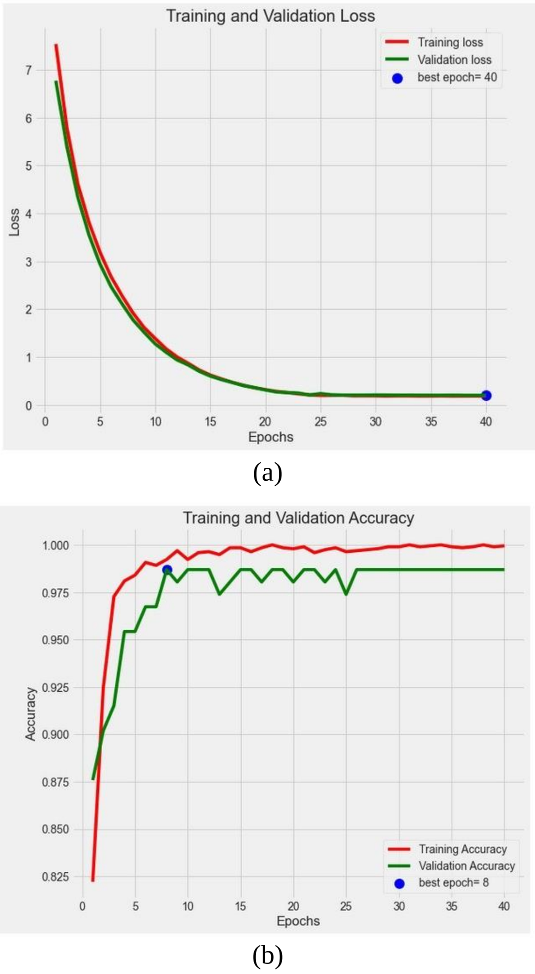

Figure 4. (a), (b) Loss dan Accuracy pada 40 epochs

3.3. Precision, Recall, F1-Score, dan Accuracy

Researchers create a confusion matrix model which is a performance measurement for classification problems where the output can be two or more classes. Table 3 shows the confusion matrix model where in Class 1 (meningioma) there are 31 TP (True Positive) values, 1 FP (False Positive) value against Class 2 (pituitary), and 0 FP (False Positive) against Class 3 (gliomata). In Class 2 (pituitary) there are 2 FP (False Positive) values against Class 1 (meningiomas), 73 TP (True Positive) values, and 0 FP (False Positive) values against Class 3 (gliomata). In Class 3 (gliomata) there are 2 FP (False Positive) values against Class 1 (meningiomas), 0 FP (False Positive) values against Class 2 (pituitary), and 45 TP (True Positive) values. True positive here means that the system predicts that the value is correct and then the prediction result is also correct. False Positive means that the system predicts that the value is wrong and then the prediction result turns out to be correct.

In class 2 actual (pituitary) and class 3 actual (gliomata) it is found that there are two data classified in class 1 prediction (meningioma), and also in class 1 actual (meningioma) there is one data classified in class 2 prediction (pituitary), According to researchers, this is because the classification engine feels confused by data with a high degree of similarity and ends up being placed in an inappropriate class, but this does not have a big effect on the final result because improper data placement only occurs in some data.

Table 4 shows the results of each Class's performance measurements. With the results as shown in table 4, it can be concluded that the process of data balancing and scaling data plays a considerable role in getting maximum results where Class 1 (meningioma) get a precision value of 89%, recall 97%, F1-score 93% and support 32. For Class 2 (pituitary) get a precision value of 99%, recall 97%, F1-score 98%, and support 75. Class 3 (gliomata) gets a precision value of 100%, recall 96%, F-score 98%, and support of 47.

Table 5 shows a comparison of accuracy between current studies and other studies where satisfactory results were found, with the method followed by Khan et al. (2021) using fine-turned VGG19, the preprocessing used was normalized intensities, and segmentation of K-means clustering found the accuracy shown in the table. In the method followed by Sunanda et al. (2019) which uses basic CNN by relying on layering and dense to get the accuracy listed in the table. Meanwhile, the method followed by Abiwinanda et al. (2019) uses basic CNN with the preprocessing used, namely hyper-parameter optimization and found the accuracy listed in the table.

Table 3. Confusion Matrix Model

Actual Predictions	Class 1. (meningioma)	Class 2 (pituitary)	Class 3 (gliomata)
Class 1 (meningioma)	31	1	0
Class 2 (pituitary)	2	73	0
Class 3 (gliomata)	2	0	45

Table 4. Performance measure

Class	Precision	Recall	F1-Score	Support
Class 1 (Meningioma)	0,061805556	0,067361111	0,064583333	32
Class 2 (Pituitary)	0,06875	0,067361111	0,068055556	75
Class 3 (Gliomata)	100	0,066666667	0,068055556	47

Table 5. Accuracy comparison among the proposed methods on the CE-MRI dataset

Method	Accuracy
Khan et al. (2021)	94.06.00
Sunanda et al. (2019)	93.33.00
Abiwinanda et al. (2019)	84.18.00
Proposed	98.00.00

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4. Conclusion

In this study, the use of the CNN Efficientnet – B3 model to classify MRI images of brain tumors, where researchers applied the scaling method as a preprocessing to the data to be used as a data train, obtained higher accuracy rate results compared to the use of methods that had been carried out in previous studies such as K-means clustering and transfer learning, which was 98.00% by using the same dataset as in table 5 of the comparison method earlier. This research still has many shortcomings and there are still many that can be improved again such as efficiency, and accuracy in the use of different datasets with more varied combinations of methods.

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