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Brain Tumor Classification Using Four Versions of EfficientNet

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Abstrak

Pendekatan pengolahan citra medis untuk mendeteksi kanker otak masih banyak dilakukan secara manual, dengan tingkat akurasi yang rendah dan waktu yang lama. Selain itu, tugas ini hanya dapat dilakukan oleh para profesional dengan kompetensi medis tingkat tinggi, dan jumlah ahli jelas terbatas dibandingkan dengan sejumlah besar pasien yang perlu dirawat. Dengan pertumbuhan kecerdasan buatan dan pesatnya perkembangan komputer dalam hal kecepatan pemrosesan dan kapasitas penyimpanan, sangat memungkinkan untuk membantu dokter dalam mengklasifikasikan keberadaan tumor di kepala. Studi ini menggunakan empat variasi arsitektur EfficientNet bertujuan untuk melatih model pada berbagai data pencitraan MRI. Model versi B1 terbukti menjadi yang terbaik dalam investigasi ini, dengan akurasi 98%, presisi 99%, recall 95%, dan skor f1 97% dari versi B0 hingga B3 (4 versi). Hasil ini sangat baik, tetapi tidak mengesampingkan studi tambahan yang menggunakan berbagai bentuk desain.

Kata kunci: Brain Tumor, EfficientNet, Deep Learning

Abstract

Medical image processing approaches for detecting brain cancers are still primarily done manually, with low accuracy and taking a long period. Furthermore, this task can only be done by professionals with a high degree of medical competence, and the number of experts is obviously restricted in comparison to the large number of patients who need to be treated. With the growth of artificial intelligence and the rapid development of computers in terms of processing speed and storage capacity, it is feasible to assist doctors in classifying the existence of tumors in the head. This study employs four variations of the EfficientNet architecture to train a model on a variety of MRI imaging data. The model version B1 was shown to be the best in this investigation, with 98% accuracy, 99% precision, 95% recall, and 97% f1 score from versions B0 to B3 (4 versions). These results are excellent, but they do not rule out additional study utilizing various forms of design.

Keywords: Brain Tumor, EfficientNet, Deep Learning

I. PENDAHULUAN

Cells are the smallest component of the human body and develop normally. When cell development exceeds normal limits (either quicker or slower), the cell is referred to be a tumor (malignant or benign). This uncontrolled cell proliferation will affect the function of the surrounding cells, resulting in a variety of human disorders [1]–[3]. A brain tumor is a group of cells that develop in the brain. Tumors that arise from the brain itself are referred to as primary brain tumors, whereas cancers that arise from other regions of the body are referred to as secondary brain tumors. After high blood pressure, stroke, diabetes, and renal disease, tumors are the fifth leading cause of mortality in Indonesia [4].

The precise etiology of tumor illness is yet uncertain [5], [6]. After Europe, Asian countries suffer the most from malignancies and have the highest death rate. According to data from the Global Cancer Observatory (GCO) for 2020 (Figure 1), there are 19.3 million tumor (cancer) patients worldwide, with 10 million dying from this disease. Breast tumour patients make up the majority of all tumour patients (11.7%), followed by lung tumour patients (11.4%), large intestine tumour patients (10%), and prostate tumour patients (7.3%). Lung tumours had the highest mortality rate (18%), followed by colon tumours (9.4%) and liver tumours (8.3%).

Asia has the biggest number of tumor patients (49%), followed by Europe (23%) [7]. Tumors kill 58% of people in Asia and 20% of those in Europe. As a result, the death ratio in Asia is greater than the death ratio in Europe. Equipment, services, and the number of experts in the health sector is still very low in Asia, the lack of medical treatment results in high death rates from this disease.

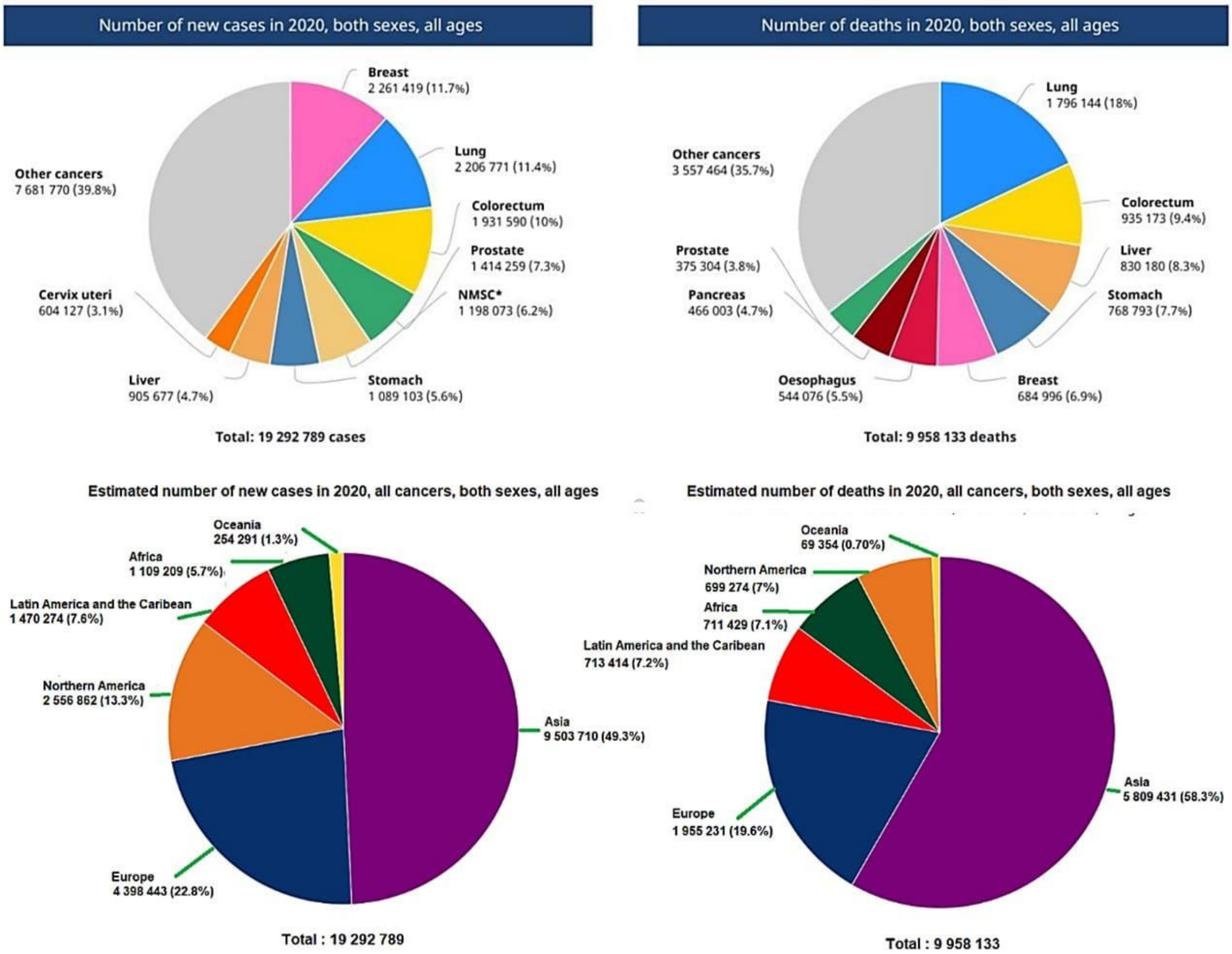

Figure 1. GCO 2020

Image datasets can be acquired using computed tomography, electroencephalography, magnetic resonance imaging, and other techniques. Magnetic Resonance Imaging (MRI) provides a high degree of accuracy and avoids the detrimental effects of radiation when compared to other image processing methods [8], [9]. To detect the existence of a brain tumor from a picture needs specialized knowledge, is costly, of poor quality, and takes a long time. Modern computer improvements have enabled high-speed processing and enormous memory storage capacity. The current fast development of Artificial Intelligence (AI) approaches, such as the Convolution Neural Network (CNN) technology, enables computers to learn from a large number of photos and detect specific things [10], [11].

This study will employ MRI image data to train the learning machine, which is the EfficientNet architecture from version B0 to B3 (4 versions). The most accurate model will be chosen to be used as a model. The chosen model may be used to determine and detect cancers in unlabeled MRI pictures in general. This training procedure employs a computer with an Intel Core i5 CPU, 16 Gb Memory, a GeForce GT 710 graphics card, Windows 10 as the operating system, and the Python programming language.

II. MATERIAL AND METHODS

The stages of work completed in this study are depicted in figure 2. Beginning with a dataset of 3929 photos, separating them into train data of 3143 images (80%) and valid data of 786 images (20%). Train data is used as input data in the training phase, while valid data is utilized to validate the model outcomes from the training process. Graphs and confusion matrices are used to represent the outcomes of accuracy measurements.

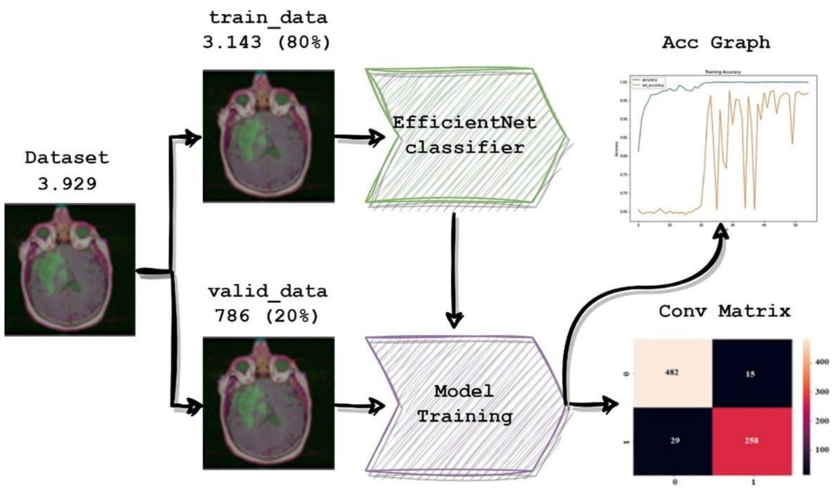

Figure 2. Proposed method

A. Dataset

The dataset was collected by downloading from the data source kaggle.com [3], consisting of 2 folders including the MRI image and image mask, and 1 file, namely "brain df.csv". The file "brain df.csv" has almost 3.900 pictures and four columns (patient id, image path, image mask, mask) (Figure 3). The mask column has the values 1 and 0. Value 1 indicates that the picture contains a tumor, whereas value 0 indicates that there is no tumor. The "brain.csv" file comprises 35% and 65% of pictures with and without tumors, respectively (Figure 4). To be able to find out the images contained in the image_path and mask_path folders, we can see some sample images in Figure 5.

	patient_id	image_path	mask_path	mask
0	TCGA_CS_5395_19981004	TCGA_CS_5395_19981004/TCGA_CS_5395_19981004_1.tif	TCGA_CS_5395_19981004/TCGA_CS_5395_19981004_1_...	0
1	TCGA_CS_5395_19981004	TCGA_CS_4944_20010208/TCGA_CS_4944_20010208_1.tif	TCGA_CS_4944_20010208/TCGA_CS_4944_20010208_1_...	0
2	TCGA_CS_5395_19981004	TCGA_CS_4941_19960909/TCGA_CS_4941_19960909_1.tif	TCGA_CS_4941_19960909/TCGA_CS_4941_19960909_1_...	0
...	...	...	...	...
3926	TCGA_DU_6401_19831001	TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_87...	TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_87...	0
3927	TCGA_DU_6401_19831001	TCGA_HT_A61A_20000127/TCGA_HT_A61A_20000127_88...	TCGA_HT_A61A_20000127/TCGA_HT_A61A_20000127_88...	0
3928	TCGA_DU_6401_19831001	TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_88...	TCGA_HT_A61B_19991127/TCGA_HT_A61B_19991127_88...	0

3929 rows × 4 columns

Figure 3. brain_df.csv

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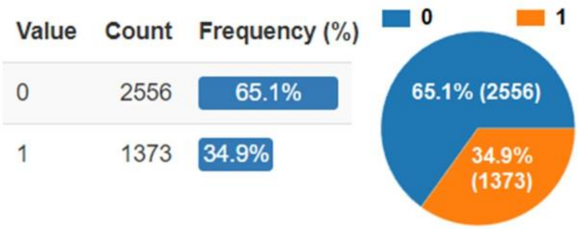
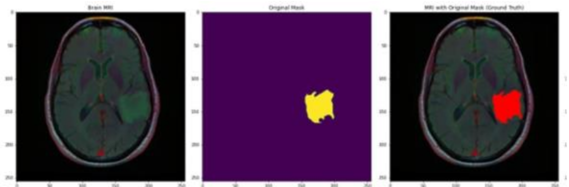
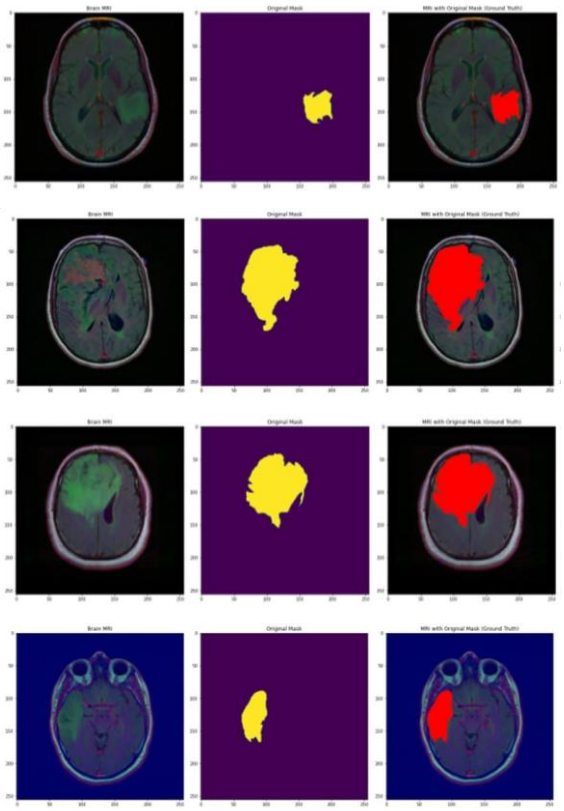


Figure 4. Number of image data containing the tumor





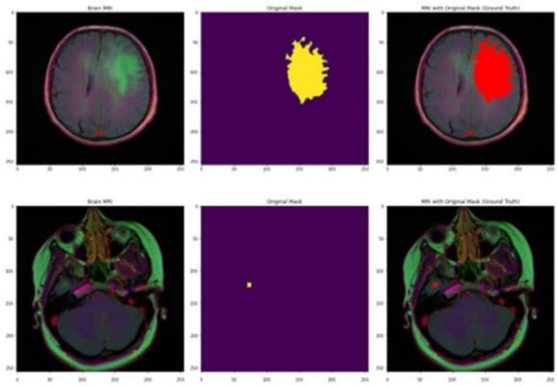


Figure 5. MRI image and mask image

B. EfficientNet

To enhance accuracy, many deep learning architectures attempt to add a growing number of layers, which reduces processing power and causes gradient descent difficulties [12]–[14]. EfficientNet, in contrast to other architectural innovations, employs a scalable and balanced increase of layer thickness and width [10], [15]. Throughout the development of each iteration, EfficientNet is able to overcome gradient descent issues, allowing it to enhance computer capabilities in obtaining high accuracy [16], [17] (Figure 6). Figure 7 depicts the EfficientNet development model.

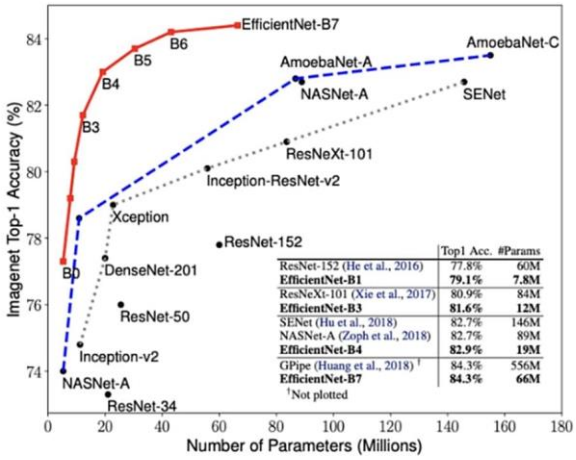


Figure 6. Comparison of EfficientNet architecture with others

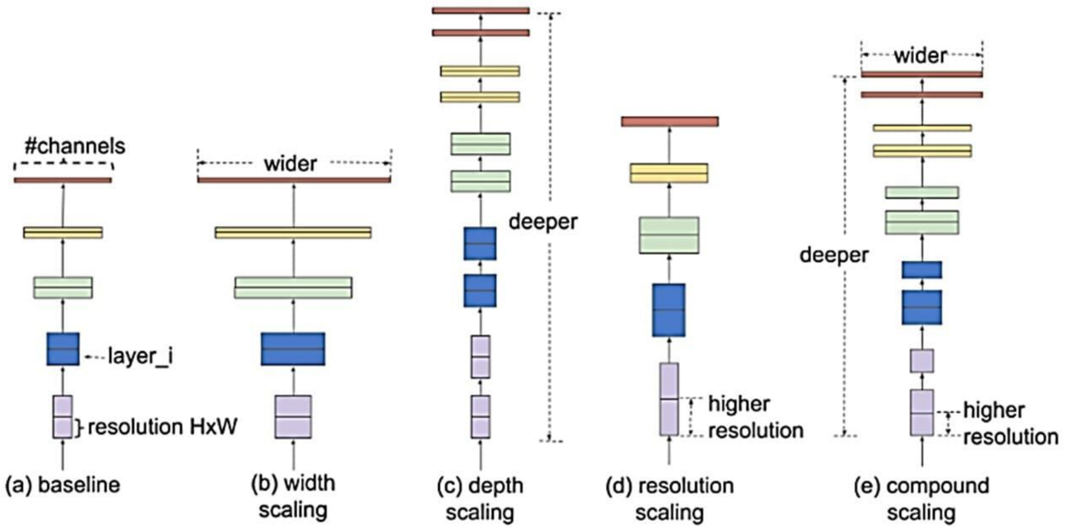


Figure 7. EfficientNet-based network [16]

Table 1 depicts the layer structure of EfficientNet, which is a collection of mobileNet architectural components [18], [19], from version B0 to B3. To achieve the convergence criterion faster in the training process, a model that was utilized in the previous training process with extremely big data is employed, which is known as the transfer learning approach. The "imagenet" transfer learning approach was employed in this investigation.

Table 1. Channel combination of 4 variants EfficientNet

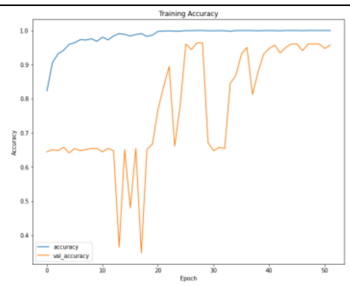
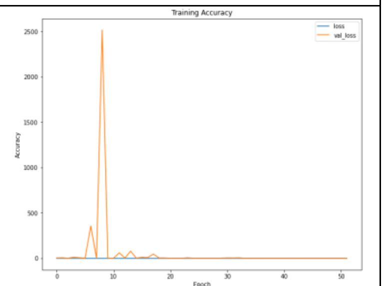
Vers	**Conv**	**MobC1 k3x3**	**MobC6 k3x3**	**MobC6 k5x5**	**MobC6 k3x3**	**MobC6 k5x5**	**MobC6 k5x5**	**MobC6 k3x3**	**Conv1x1 +Pool+FC**
B0	32	16	24	40	80	112	192	320	1280
B1	32	16	24	40	80	112	192	320	1280
B2	32	16	24	48	88	120	208	352	1408
B3	40	24	32	48	96	136	232	384	1536

III. EXPERIMENTAL RESULTS AND DISCUSSION

The results of the training process for the classification of the presence of tumors in the head are expressed in the form of training graphics for accuracy, training loss and confusion matrix for the use of 4 types of machine learning from the version available on EfficientNet (Figure 8, and Figure 9).

Formulas 1, 2, 3, and 4 are utilised to numerically calculate the outcomes utilising 5 variables (precision, recall, f1 score, support, and accuracy). The computation's outcomes are displayed in table 2.

To calculate the results numerically using 5 variables (precision, recall, f1 score, support, and accuracy), a formula is used as shown in figure 10. The calculation results can be seen in table 2.

Versi	**Acc**	**Loss**
B0		

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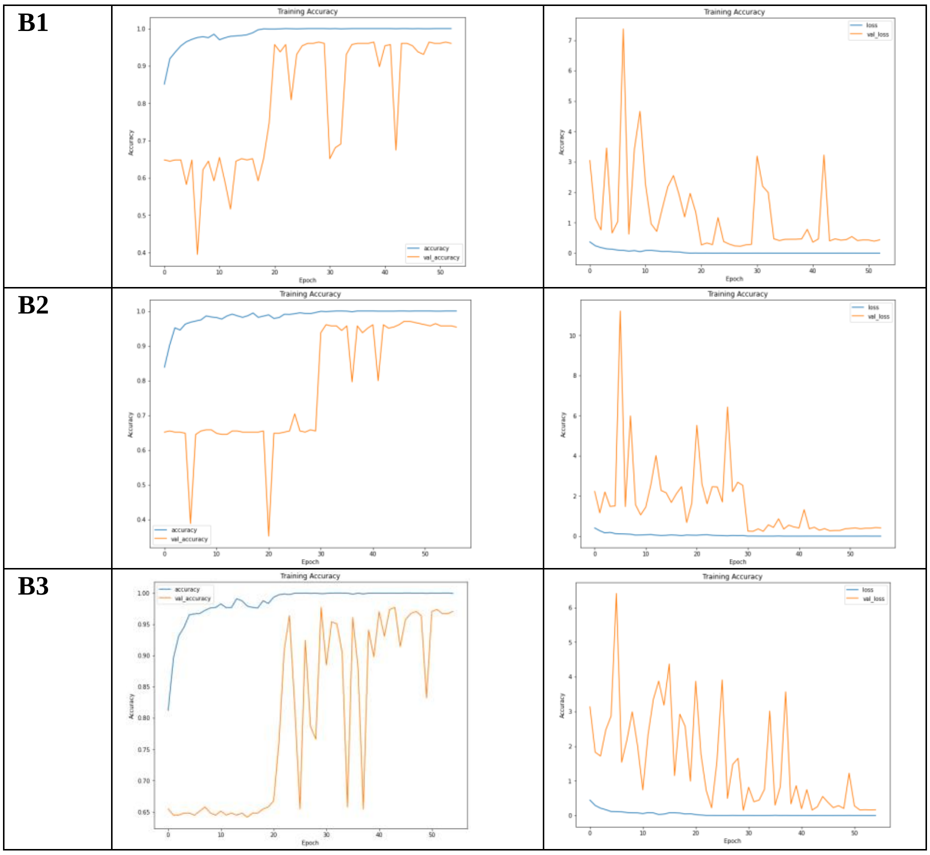


Figure 8. The results of the training are in the form of graphs

Confusion Matrix

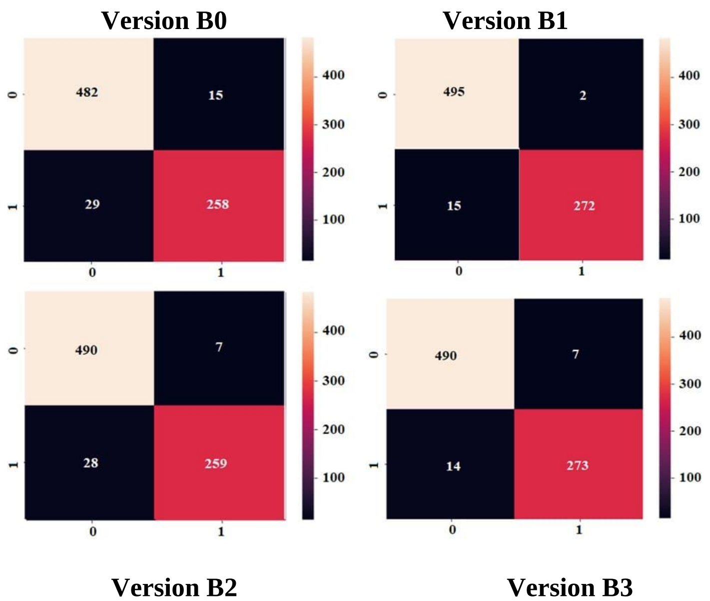


Figure 9. The results of the training are in the form of confusion matrices

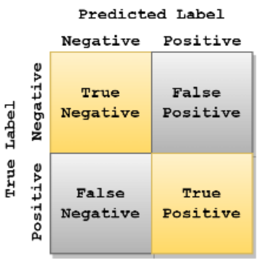
There are various measurement methods to evaluate the results of the classification process. A very common one is the confusion matrix [19][20] (Fig. 8).

By looking at the confusion matrix (Figure 8), the desired result is the highest possible True_Negative (TN) and True_Positive (TP) values, and the lowest possible False_Negative (FN) and False_Positive (FP) values. Precision is used to show the trade-off in the model between the sensitivity of detecting TP while balancing the number of FPs [20], [21]. It is given by equation (1) as follows

Furthermore, we can define the true positive rate (TPR) which is called recall with equation (2) [22]. Used to demonstrate the model's ability to detect positive cases in the following data sets:

Accuracy is the distribution of correct model predictions [23] and is expressed by equation (3) as follows:

F1-score is a combination of precision and recall [24] and is expressed by equation (4) as follows:



$$Prec = \frac{TP}{TP + FP} \dots\dots\dots (1)$$

$$Rec = \frac{TP}{TP + FN} \dots\dots\dots (2)$$

$$F1\ Score = 2 * \frac{Prec * Rec}{Prec + Rec} \dots\dots\dots (3)$$

$$Acc = \frac{TN + TP}{TN + FP + TP + FN} \dots\dots\dots (4)$$

Tabel 2. Measurement results of prec, rec, f1 score, support, and acc

Ver	acc	prec	rec	f1_score
B0	0.94	0.95	0.90	0.92
B1	0.98	0.99	0.95	0.97
B2	0.96	0.97	0.90	0.94
B3	0.97	0.97	0.95	0.96

IV. CONCLUSION

The best model generated from the research by carrying out the training procedure utilizing four versions of the EfficientNet architecture is version B1, with an accuracy value of 98%, precision of 99%, recall of 95%, and f1 score of 97%. Considering the four model versions tested yielded high accuracy values (> 90%), all models developed may be classified as very excellent.
Versioning tries to add layers in order to attain a high accuracy rating, yet it can be observed that a higher version does not necessarily give better accuracy. It has been demonstrated that the B1 version (the lesser version of B2 and B3) produces the best model results.
To develop a model that can be applied in general, further study must be conducted utilizing various types of architecture or more sophisticated data. As a result, more study may be conducted by carrying out this type of training method (brain tumor classification).

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