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Classification of Brain Image Tumor using EfficientNet B1-B2 Deep Learning

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Abstract
In this study, a new neural network model (EfficientNet B1-B2) was sought for the detection of brain tumors in magnetic resonance imaging (MRI) images. The primary objective was to achieve high accuracy rates so as to classify the images. The deep learning techniques meticulously processed and increased the data augmentation as much as possible for the EfficientNet B1-B2 models. Our experimental results show an accuracy of 98% in the B1 version in Table II. This provides a potentially optimistic view of the application of artificial intelligence technology to disease diagnosis based on medical image analysis. Nonetheless, we must remind ourselves that the dataset we used has limitations in terms of the challenges it can pose. Although the number of potential variations of actual medical images constitutes a major challenge, it is not the only one. Most medical datasets are unbalanced, contain highly variable noise, have a slow internal structure, and are often small in size. Hence, our end goal is to help stimulate not only the field of brain tumor detection and treatment but also the development of more sophisticated classification models in the health context.

INTRODUCTION

In the domain medical research, early detection and classification of brain tumors is a critical challenge that affects the treatment and prognosis of patients (Rao & Karunakara, 2022). Deep learning algorithms, especially EfficientNet, have emerged as a promising solution for dealing with the complexities of analyzing medical images (Farhat et al., 2020). By combining high pattern recognition capabilities and computational efficiency, EfficientNet is able to recognize complex variations and characteristics of brain tumors, even in large and varied medical images (Shah et al., 2022). This model can automatically extract complex features that may be difficult for the human eye to identify. The use of this algorithm in brain tumor classification can help doctors to make decisions based on more in-depth and accurate information (Nayak et al., 2022).

Speed and accuracy are key aspects in brain tumor detection (Ren et al., 2023). EfficientNet was able to overcome this challenge by optimizing performance and efficiency (Shah et al., 2022). Careful computational modeling allows for rapid response to a given medical image, which could ultimately contribute to earlier and more successful treatment (Panayides et al., 2020). In addition, the implementation of this algorithm facilitates personalized treatment by recognizing the unique features of each tumor (Adir et al., 2020). By identifying the unique characteristics of each tumor, doctors can design treatment strategies that are better suited to the patient's condition (Schmidt et al., 2020). This minimizes the risk of overuse or ineffective medication.

Research related to brain tumors using deep learning methods has attracted the interest of world researchers (Dang et al., 2022; Demir et al., 2023; Emam et al., 2023; Farajzadeh et al., 2023; Kanchanamala et al., 2023; Mehnatkesh et al., 2023; Tabatabaei et al., 2023). Previous research used the Convolutional Neural Networks (CNN) method with the EfficientNet architecture (Isunuri & Kakarla, 2023; Nayak et al., 2022; Shah et al., 2022; Tripathy et al., 2023; Zulfiqar et al., 2023), multi-class Support Vector Machine (SVM) and fuzzy classifier (Vankdothu & Hameed, 2022), hybrid model combined CNN and SVM (Khairandish et al., 2022), SVM and Artificial Neural Network (ANN) (Sachdeva et al., 2016), hybrid machine learning (ML) *k*-nearest neighbour and *k*-means clustering (Rinesh et al., 2022), accelerated particle swarm optimization (APSO) based artificial neural network model (ANNM) (Pradeep et al., 2022), particle swarm optimization (PCA) algorithms (Zahid et al., 2022), atomic force microscopy (AFM) (Huml et al., 2023), CNN-pretrained ResNet-50, Inception-v3, and VGG-16 (Srinivas et al., 2022), Genetic Algorithm and U-Net (Arif et al., 2022).

With the application of the efficientNet algorithm in brain tumor classification, medical professionals have a powerful tool for medical image interpretation. This not only increases the accuracy of the diagnosis but also assists them in planning more effective treatment. In addition, the role of this technology in managing complex medical image data is invaluable in lightening the workload of medical professionals. This study aims to classify brain tumors using the efficientNet architecture B1-B2.

RESEARCH METHODS

The initial process at this stage starts from downloading the dataset obtained from kaggle.com (Chakrabarty, 2019) with a total of 3,929 images (figure 2). The dataset is divided into 0.8 training data and 0.2 image test data, Valid data is used to verify the model outputs after training, while training data is utilised as input during training. The dataset is in csv format, consisting of two image mask folders and Magnetic Resonance Imaging (MRI) images and one file df.csv which has four columns and 3,929 rows, shown in Figure 1. The operating environment used in this experiment is the Intel Core i5 generation. 10300, 32GB RAM, GTX 1650, 512GB SSD. The development environment uses anaconda, python language with Jupyter notebook editor, tensorflow framework and Keras.

	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 1. Extract the brain df.csv file

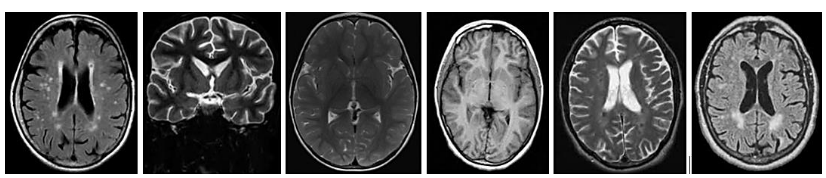


Figure 2. Image dataset

The experimental flow is shown in Figure 3, starting with data preprocessing, including image resizing, pixel normalization, and dividing the dataset into training data, validation data, and test data. Followed by the process of selecting the EfficientNet model according to the size of the dataset and the complexity of the task. In building and training the EfficientNet model using the TensorFlow library, determines, following establishing the model with pre-trained weights, determines the loss and optimizer functions to be used during training. Train the model with training data and monitor evaluation metrics such as accuracy and loss in validation data to avoid overfitting. The loss function is used to measure how well the model that has been made matches the training data. For this classification task, we use Cross-Entropy Loss (log loss) as the default loss function. To optimize the performance of the model, hyperparameter tuning is carried out, such as epoch count, batch size, and learning rate.

This experiment uses the RMSProp optimizer, this algorithm was developed to overcome some of the problems encountered by other optimization algorithms such as SGD (Stochastic Gradient Descent). The main goal of RMSProp is to overcome problems with unstable learning rates in SGD, which can lead to slow or even non-converging training. RMSProp tries to overcome this problem by adapting the learning rate for each parameter based on the historical change of the gradient. Evaluate the model on the test data to get an overview of the model's performance, by using a confusion matrix and calculating metrics such as accuracy, precision, recall, and F1-score. Visualization of results using an accuracy graph. With this information, several important evaluation metrics can be calculated;

- Accuracy measures the extent to which the model successfully predicts correctly among all the predictions made. Accuracy is calculated as (TP + TN) / (TP + FP + TN + FN). (1)
- Precision measures the extent to which the positive predictions made by the model are correct. Precision is calculated as TP / (TP + FP). (2)
- Recall or Sensitivity: Recall measures the extent to which the model can correctly detect positive data. Recall is calculated as TP / (TP + FN). (3)
- F1-score: is the harmonic average between precision and recall. This is useful when looking to strike a balance between precision and recall. F1-score is calculated as 2 * (presisi * recall) / (presisi + recall). (3)

Discussion of the results of the Confusion Matrix EfficientNet will involve analysis of accuracy, precision, recall, and F1-score. If the model has good performance, it will have high accuracy, precision, recall, and F1-score values. However, if there are problems such as overfitting or bias in the dataset, the model's performance may suffer, and further analysis is needed to understand the cause and take steps for improvement. A mobileNet is a collection of the efficientNet layer's design, a design features from version B1 to B2, is presented in Table 1.

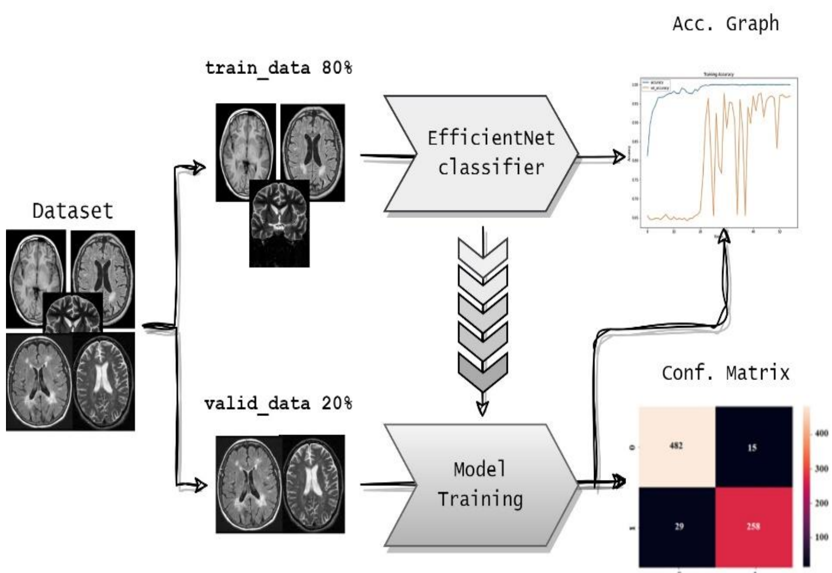


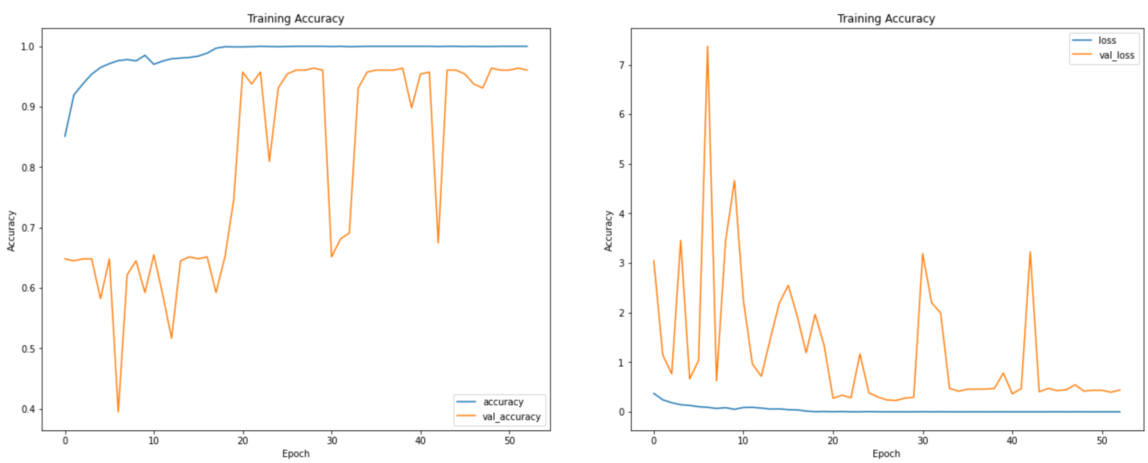
Figure 3. Experiment flow

Table 1. Two versions combined in a channel EfficientNet B1-B2

Stage *i*	**Operator** *Fi*	**Resolution** *Hi x Wi*	**Channels** *Ci* **(B1)**	**Channels** *Ci* **(B2)**
1	Conv	224 x 224	32	32
2	MobC1 k3x3	112 x 112	16	16
3	MobC6 k3x3	112 x 112	24	24
4	MobC6 k5x5	56 x 56	40	48
5	MobC6 k3x3	28 x 28	80	88
6	MobC6 k5x5	14 x 14	112	120
7	MobC6 k5x5	14 x 14	192	208
8	MobC6 k3x3	7 x 7	320	352
9	Conv 1x1 + Pool + FC	7 x 7	1280	1408

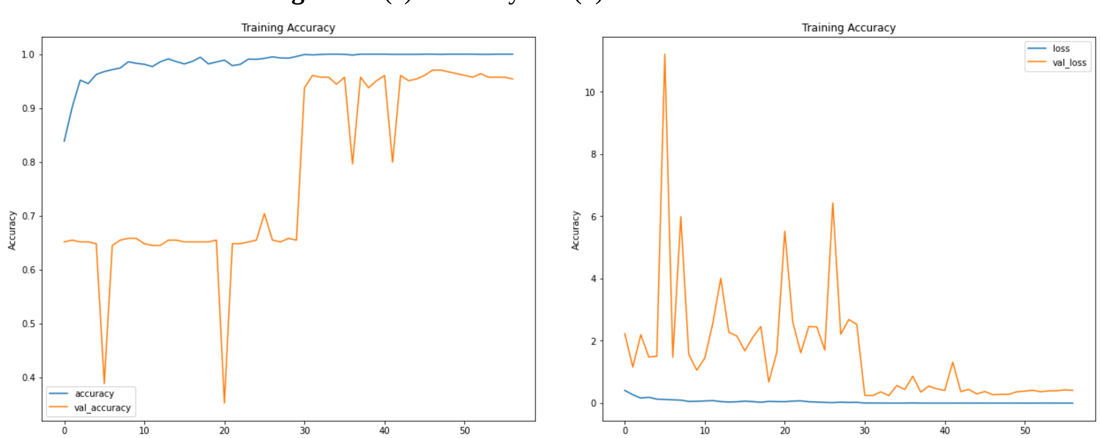
RESULTS AND DISCUSSION

The use of instruction graphs to see the results of accuracy, confusion matrix and training loss in the function of the efficientNet model. The results of the training process for tumor classification are shown in Figures 4 and 5. A formula is utilised as illustrated in figure 6 to quantitatively calculate the outcomes utilising the five factors (support, accuracy, recall, f1 score and precision). Table 2 displays the calculation's findings.



(a) (b)

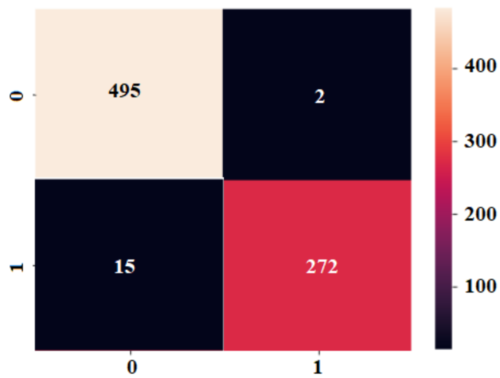
Figure 4. (a) Accuracy and (b) Loss EfficientNet B1



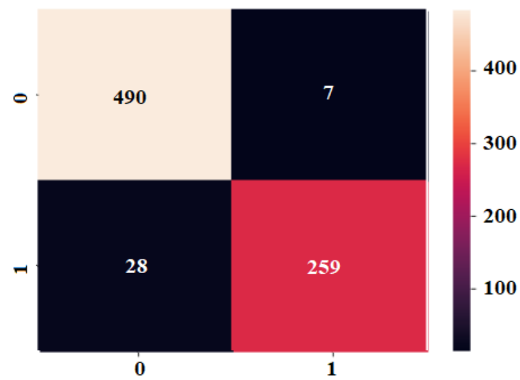
(a) (b)

Figure 5. (a) Accuracy and (b) Loss EfficientNet B2

The results of experiments that have been carried out with a small learning rate, such as 0.001, this serves to control how much each change in model parameters is made during training. Starting with Batch sizes 16 and 32, to balance training speed and memory usage. Larger batch sizes can increase training speed because more computations are performed in parallel. However, too large can cause GPU memory to run out. The number of epochs refers to the number of times the entire dataset is given to the model, this experiment uses 60 epochs and it is necessary to pay attention to the model's performance on validation data. Sometimes, performance improvement stops after a few epochs, but if performance continues to improve on validation data, then you can try increasing the number of epochs.



(a)



(b)

Figure 4. Confusion Matrix (a) EfficientNet B1 and (b) EfficientNet B2

Table 2. Comparison of the experimental results of EfficientNet B1-B2

Version	Accuracy	Precision	Recall	f1-score
B1	**0.98**	**0.99**	**0.95**	**0.97**
B2	0.96	0.97	0.90	0.94

In this experiment, we managed to achieve a high accuracy rate of 98% on the EfficientNet B1 model. This is an impressive achievement and demonstrates the model's ability to classify images with very high accuracy. In this study, we use the EfficientNet B1 and B2 model architectures, which are more complex variants of the EfficientNet architecture. We ensure that the dataset used is large enough and includes a wide variety in the images classified. Good and representative data allows the model to learn patterns better. Careful data preprocessing, including pixel normalization and data augmentation. Proper preprocessing helps the model learn better and reduces the risk of overfitting.

We perform tuning on hyperparameters such as batch size, number of epochs, and learning rate. This allows the model to converge properly and avoid overfitting problems. Carefully monitor model performance during training using validation data. This allows us to quickly detect signs of overfitting or underfitting and take the necessary action. This 98% accuracy result is proof of the effectiveness and adaptability of the EfficientNet model in image classification tasks. Referring to the experimental results summarized in table 2, EfficientNet version B1 is more optimal than version B2, with an accuracy of up to 98%.

Comparison of current model performance studies, summarized in table 3. Studies that have been conducted by (Nayak et al., 2022) To categorise the various forms of brain tumours with 98.78% accuracy, the authors utilised dense EfficientNet with min-max standardisation, which is superior to other related studies using the same dataset. The EfficientNet-B0 to EfficientNet-B7 model was implemented in the study's findings, and the EfficientNet-B2 model's use of transfer learning enabled the classification achieve superior results in the deep learning sector, with the best accuracy results reaching 96% (Zhaputri et al., 2021). Classification of tumors by

(Zulfiqar et al., 2023) The use of the EfficientNetB2 architecture achieves optimal results (98.86%), fast computing processes, and has optimal performance on a single platform.

Research conducted by (Tabatabaei et al., 2023) proposed a more compact and enhanced CNN architecture (iResNet) that will recognize tumor features from MR images CNN iVGG, iDensNet, and iResNet with the best results reaching 99.30% with the iResNet model. Research conducted by (Isunuri & Kakarla, 2023) For the grade classification, suggest an EfficientNet and multi-path convolution with a multi-head attention network. When extracting features, employed an EfficientNetB4 that had already been trained. Then, a feature enhancement task is carried out using a multi-path convolution with a multi-head attention network. It uses the EfficientNet-B4 model with the best performance of 98.35%.

The ResNet50, EfficientNetB1, EfficientNetB7, and EfficientNetV2B1 architectures are used in the research results (Filatov & Yar, 2022), with the EfficientNetB1 model having the best accuracy (89.55%). Small picture augmentation and transfer learning were applied to reduce the negative effects of a dataset and insufficient computational capability. Accuracy reaches 96.94% with the EfficientNet-B0 model. The Magnetic Resonance Images (MRI) have been loaded into EfficientNet, which continuously adds hidden layers to increase efficiency (Goutham et al., 2022). Research that has been conducted by (Lakshmi Veeranki et al., 2023) uses the EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16 models, using Transfer Learning with the best results using the EfficientNet-B0 model of 97.61%.

Table 3. Performance study of present models

Reference	Methods	Results
(Nayak et al., 2022)	Dense EfficientNet, ResNet50, MobileNet, MobileNetV2	optimum accuracy model Dense EfficientNet 98.78%
(Zhaputri et al., 2021)	EfficientNet-B0 to EfficientNet-B7	optimum accuracy model EfficientNet-B2 96%
(Zulfiqar et al., 2023)	EfficientNet-B0 to EfficientNet-B4	optimum accuracy model EfficientNet-B2 98.86%
(Tabatabaei et al., 2023)	iVGG, iDensNet, and iResNet	optimum accuracy model iResNet 99.30%
(Isunuri & Kakarla, 2023)	EfficientNet-B4 and multi-path convolution with a multi-head attention network model	optimum accuracy model EfficientNet-B4 98.35%
(Filatov & Yar, 2022)	ResNet50, EfficientNetB1, EfficientNetB7, EfficientNetV2B1	best accuracy EfficientNetB1 89.55%
(Goutham et al., 2022)	EfficientNet-B0	best accuracy 96.94%
(Lakshmi Veeranki et al., 2023)	EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16, using Transfer Learning	optimum accuracy model EfficientNet-B0 97.61%
Proposed models	EfficientNet B1-B2	accuracy 98% and 96%.

CONCLUSION

In this study, we managed to achieve an impressive accuracy rate of 98% on the EfficientNet B1 model. These results demonstrate the tremendous potential of this model in the image classification task. Through careful experimentation and effort, we were able to identify several key factors that contributed to this high accuracy result. EfficientNet's model architecture has proven to be very effective in learning complex image representations. With an accuracy rate of 98%, these results provide strong evidence of the model's ability to classify various objects in MRI images. Well-managed and representative datasets play a crucial role in achieving this level of accuracy.

The presence of sufficient variation in the dataset allows the model to understand and recognize the various patterns that may emerge in the new data. Medical images of brain tumors have many variants in terms of size, shape and location, which makes them difficult to analyze manually. In this case, EfficientNet plays a central role by being able to automate the classification process. The use of EfficientNet enables early detection of brain tumors with a high degree of accuracy and efficient computational time. In the case of brain cancer, time is precious. Early detection can accelerate clinical response and more timely treatment, increase chances of cure and reduce patient harm. Nonetheless, we recognize that each model has its own limitations, and there are some challenges that may have to be overcome in real-world scenarios. However, this success provides a solid basis for further research and application of the model in various domains.

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