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Multiclass Classification of Brain Tumors in MRI Images Based on Deep Learning

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ABSTRACT
Brain tumors are one of the most deadly neurological diseases that require early and accurate diagnosis to determine the right treatment plan. The use of Magnetic Resonance Imaging (MRI) images is the standard in detecting brain tumors, but manual classification by radiologists is time-consuming and has a high risk of subjectivity. This study focuses on the classification of four main categories: glioma, meningioma, pituitary tumor, and healthy brain tumor (not a tumor). This study aims to build an automatic multi-class classification system for brain tumors using a Deep Learning approach with MobileNetV2 and EfficientNetB0 architectures. The training process is carried out using transfer learning techniques and learning rate optimization through system callbacks to ensure the model reaches the best convergence point. The results show that the proposed model is capable of classification with very high performance, achieving an accuracy of 96.88%. The evaluation results using a confusion matrix indicate that the model has a consistent ability to distinguish between tumor classes with an average F1 score of 0.97.

Keywords: *MRI image, Convolutional Neural Network Deep Learning,Transfer Learning,Brain Tumor*

ABSTRAK
Tumor otak merupakan salah satu penyakit neurologis paling mematikan yang membutuhkan diagnosis dini dan akurat untuk menentukan rencana pengobatan yang tepat. Penggunaan citra Magnetic Resonance Imaging (MRI) merupakan standar dalam mendeteksi tumor otak, tetapi klasifikasi manual oleh ahli radiologi memakan waktu dan memiliki risiko subjektivitas yang tinggi. Studi ini berfokus pada klasifikasi empat kategori utama: glioma, meningioma, tumor hipofisis, dan tumor otak sehat (bukan tumor). Studi ini bertujuan untuk membangun sistem klasifikasi multi-kelas otomatis untuk tumor otak menggunakan pendekatan Deep Learning dengan arsitektur MobileNetV2 dan EfficientNetB0. Proses pelatihan dilakukan menggunakan teknik transfer learning dan optimasi laju pembelajaran melalui callback sistem untuk memastikan model mencapai titik konvergensi terbaik. Hasil menunjukkan bahwa model yang diusulkan mampu melakukan klasifikasi dengan kinerja yang sangat tinggi, mencapai akurasi 96,88%. Hasil evaluasi menggunakan matriks kebingungan menunjukkan bahwa model memiliki kemampuan yang konsisten untuk membedakan antara kelas tumor dengan skor F1 rata-rata 0,97.

Kata Kunci : *MRI image, Convolutional Neural Network Deep Learning,Transfer Learning,Brain Tumor*

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1. INTRODUCTION

In the medical world, particularly in the diagnosis of brain diseases such as glioma, pituitary tumors, and meningiomas, human interpretation of medical images is often limited by subjectivity and uncertainty. The main challenge arises from the visual similarities between these types of brain tumors. Therefore, a more objective and consistent solution is needed for the recognition and classification of brain diseases through medical images [1]. According to medical data, brain tumors such as gliomas, meningiomas, and pituitary tumors require different treatment strategies, ranging from surgery to radiotherapy. Therefore, early identification and accurate classification of tumor type are key to determining the appropriate medical procedure [2].
Magnetic resonance imaging (MRI) is the primary tool in this screening process. However, the large volume of MRI data and the visual complexity between healthy tissue and early-stage tumors often

make manual observation difficult [3]. Therefore, a classification system is needed that is not only able to differentiate between tumor types, but is also able to verify images that show normal brain conditions [4].
As a solution to these constraints, this research leverages advances in Deep Learning technology through the implementation of a Convolutional Neural Network (CNN) architecture that boasts superior capabilities in automatically extracting spatial features. The problem-solving plan focuses on the use of the EfficientNet-B1 architecture, which is theoretically superior to traditional CNN architectures due to its application of the compound scaling principle [5].

Research by Maqsood, Robertas Damaševiˇcius and Rytis Maskeli ¯ unas in 2022, on the classification of brain tumors using deep learning and SVM results showed that the proposed method for detecting and classifying brain tumors outperformed other methods both visually and quantitatively, achieving an accuracy of 92.47% each. However, the proposed model is still traditional [6]. Another study by Gómez-Guzmán in 2025, The proposed approach leverages the publicly accessible Msoud Brain Tumor MRI dataset,
consisting of 7023 images, with 5712 provided for training and 1311 for testing. The results highlight the strong potential of a pre-drilled deep, transformer-based CNN architecture achieving the highest classification accuracy of 90.24% on the testing dataset using 75% of the training data. in medical image analysis. The proposed approach provides a scalable and energy-efficient solution for automated brain tumor diagnosis, facilitating the integration of AI into clinical workflows. The proposers are confident that the accuracy of future studies will be even better [7].
The theoretical basis of this research is based on the concept of convolution in digital image processing and the Mobile Inverted Bottleneck Convolution (MBConv) mechanism which is the backbone of EfficientNet-B1 [8]. Theoretically, the use of 240 x 240 pixel input resolution in this model provides an optimal detail ratio for detecting vague tumor boundaries. The use of pre-trained weights from ImageNet is expected to provide an understanding of universal features that will then be specialized in the radiology domain through a fine-tuning process. The hope of this research is to produce a classification model capable of achieving an accuracy level above 97%, thus providing practical benefits as an objective initial screening tool for medical practitioners. The success of this research is expected to minimize the number of false positives and false negatives, which will ultimately increase the efficiency of diagnostic procedures in healthcare institutions.

2. RELATED WORKS

This literature review summarizes several previous studies related to brain image classification. This description aims to strengthen the theoretical foundation and provide an overview of the current research's position in comparison to the existing literature.
Previous research by Dede Husen in 2024, this study aims to improve the accuracy of brain tumor classification using the Convolutional Neural Network (CNN) method on Magnetic Resonance Images (MRI) images. The dataset used is a public dataset from Kaggle, which contains four classes of tumors: glioma, meningioma, notoma, and pituitary tumor. The data augmentation techniques applied include inverting (flipping), scaling (scaling), random brightness (random brightness), random rotation (random rotation), and combined augmentation techniques to enrich the training dataset. The results of the study showed that data augmentation can significantly improve the accuracy of the CNN model. The best model was obtained using the combined augmentation technique of inverting and scaling, resulting in an average accuracy of 92.97%. However, this study only discusses the differences in the types of image augmentation on the accuracy of the model [9].
Further research by Mohamed A. Sayedelahl in 2025, this study presents an integrated deep learning approach that combines augmentation, segmentation, and classification techniques to identify various tumor types in skin lesions and brain MRI scans. Our method uses a refined InceptionV3 convolutional neural network and is trained on a multi-modal dataset consisting of dermatoscopic images from the Human Against Machine archive and brain MRI scans from the ISIC 2023 repository. To address all classes, advanced preprocessing and Generative Adversarial Network (GAN)-based augmentation are applied. This model achieves 93% accuracy in classifying

images across ten categories: seven types of skin cancer, several brain tumor variants, and an "undefined" class. The difference from the proposed study lies in the small dataset and the need for image augmentation to achieve class balance [10].
Another study by Noviyanto in 2025, this study compared the performance of four transfer learning-based Convolutional Neural Network (CNN) models: DenseNet121, InceptionV3, MobileNet, and Xception, in classifying brain tumors using MRI images. The novelty of this study lies in the use of a larger MRI dataset and a more diverse multiclass classification scheme, namely four classes of brain tumors, so that the evaluation model becomes more representative of real-world clinical conditions. The experimental results showed that all models achieved accuracy above 90%, with MobileNet showing the best performance with an accuracy of 94.74%, and precision, recall, and F1-score of 0.95, 0.95, and 0.94, respectively [11].
The latest research by Candra F et al. in 2024. This research focused on one of the pre-trained CNN models, VGG-16. VGG-16 is a CNN with 16 convolutional layers; deeper convolutional layers improve classification results. The results showed that VGG-16 can achieve prediction accuracy of up to 97%, providing positive hope for improving the effectiveness of brain tumor diagnosis and treatment through the application of advanced technologies such as deep learning. However, the dataset used was less diverse, resulting in a lack of dataset generalization [12].
Based on a review of several previous studies, there are research gaps that are the main focus of this study. Although the research of Husen (2024) and Sayedelahl (2025) has demonstrated the effectiveness of augmentation techniques and the use of GANs to improve accuracy, both still face constraints such as limited dataset size and unrepresentative data variation. On the other hand, the use of large model architectures such as VGG-16 by Candra F et al. (2024) is indeed able to achieve high accuracy of 97%, but the model has large parameter redundancy, making it computationally inefficient. Meanwhile, research by Noviyanto (2025) which evaluated transfer learning models such as MobileNet provides a lighter alternative, but still has room for accuracy optimization through more modern architectures. Therefore, this study aims to address these limitations by implementing the EfficientNet-B1 architecture, which uses compound scaling to balance model depth and efficiency. Supported by the use of a large-scale dataset, this study is expected to overcome the generalization issues encountered in previous studies while producing more accurate and efficient brain tumor classification performance.

3. METHOD

3.1. Research Flow

The stages of this research were systematically structured to ensure the brain tumor classification process followed the correct methodology. The research process began with problem identification, large-scale dataset collection, and the evaluation of the EfficientNet-B1 model. These stages are visually depicted in the flowchart in Figure 1 below.

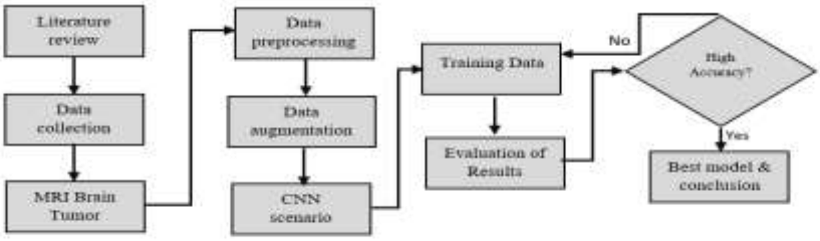


Figure 1. Research Flow

This research flow is systematically designed, starting with the Literature Review stage to explore theories and findings from previous research, followed by Data Collection to gather the necessary data assets. The collected data, namely MRI Brain Tumor images, enters the Data Preprocessing stage to be cleaned and formatted, and the Data Augmentation stage to increase the variety and volume of the dataset to make the model more robust. Once the data is ready, a CNN Scenario is compiled using the EfficientNet-B1 architecture, which is then implemented into the Training Data stage. The results of the training then enter the Evaluation of Results stage to test its performance. If the evaluation results do not meet the High Accuracy criteria, the process will return to the training stage for re-optimization.

However, if high accuracy has been achieved, the process will end with the determination of the Best Model and the drawing of Conclusions as the final result of the research.

3.2. Data Collection
Data collection is the stage of gathering the dataset that will be used in the research. The dataset used is secondary data on brain tumors with MRI images taken from a public Kaggle dataset called Brain Tumor MRI Dataset with the URL Dataset https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset. This dataset consists of four image classes: Glioma Tumor, Meningioma Tumor, Normal (No Tumor), and Pituitary Tumor, with a total of 516 MRI images in the .jpg file extension [13]. Examples of image data for each class are shown in Figure 2.

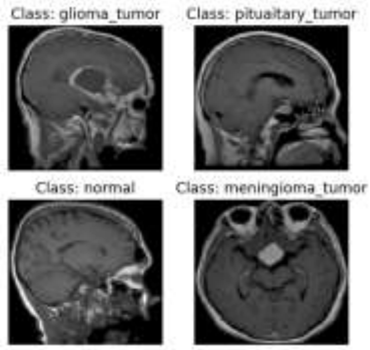
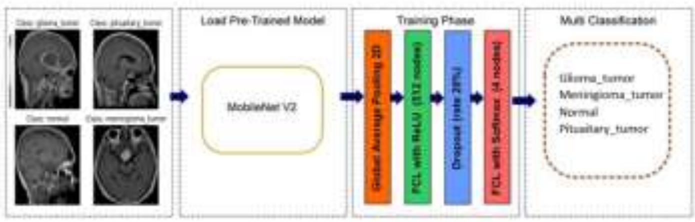
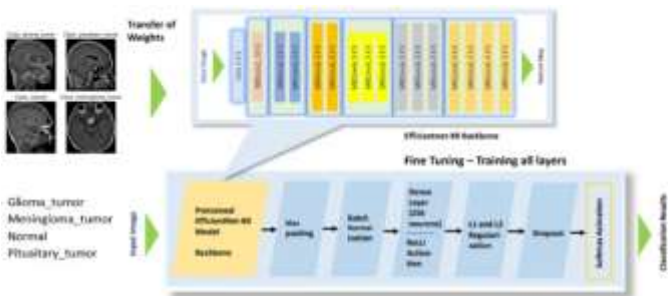


Figure 2. Brain Tumor MRI Dataset

3.3. Model Architecture
Data CNN, short for Convolutional Neural Network, is a type of deep neural network commonly used for image recognition and processing. CNN is often used to recognize objects or detect specific features in images [14]. The model will be trained using a pre-trained model developed by the proposer and the CNN architecture development will adopt transfer learning from popular architectures, namely MobileNetV2 and EfficientNetB0 [15]. Then, from the transfer learning model, 1 convolutional layer, max pooling, dropout, flatten, and finally a dense layer are added to each model. The model summary is in Figure 3.



(a)



(b)

Figure 3. Model Summary MobileNetV2 and EfficientNet-B0 for Brain Tumor MRI Dataset

In figure 3.This model processes MRI images into four categories glioma, meningioma, pituitary, and normal by relying on MobileNetV2 as the main feature extractor known to be very lightweight and efficient. After passing through the Load Pre-Trained Model stage, the data is streamed into the training phase consisting of a 2D Global Average Pooling layer to simplify the feature data, followed by a Fully Connected Layer (FCL) containing 512 nodes with ReLU activation to learn complex patterns. To prevent overfitting, a Dropout layer of 20% is applied before finally reaching the Softmax layer with 4 nodes responsible for producing the final prediction probability to determine the type of tumor or the patient's brain condition [16]. Utilizes the EfficientNet-B0 architecture through a Transfer Learning approach. The process begins by taking a model that already has trained weights (Transfer of Weights) to recognize basic visual patterns, then performing feature extraction using the MBConv block with filter variations of 3 X 3 and 5 X 5. To optimize accuracy in medical cases, this model applies a Fine Tuning strategy to all layers combined with additional Head structures in the form of Max Pooling, Batch Normalization, and a Dense Layer with 256 neurons. The use of ReLU activation, L1/L2 regularization techniques, and Dropout serves to maintain training stability and prevent overfitting [17]. This flow ends with a Softmax Activation layer that produces the final classification probabilities into four categories: glioma, meningioma, pituitary tumor, or normal brain condition.

3.4. Confusion Matrix

The confusion matrix is used as a tool to assess the performance of a classification model, consisting of four main elements. True Positives (TP) refers to the number of cases in which the model successfully predicts data as positive. True Negatives (TN) reflect the number of correct predictions when the model identifies data as negative. False Positives (FP) occur when the model incorrectly identifies negative data as positive. Meanwhile, False Negatives (FN) indicate the number of errors when the model fails to recognize positive data and instead classifies it as negative [18]. Based on these four components, model performance can then be evaluated through various evaluation matrices.

a. Akurasi $$Akurasi = \frac{\text{Jumlah Prediksi Benar}}{\text{Total Data}} \quad (1)$$

b. Presisi $$Presisi = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Positive\ (FP)} \quad (2)$$

c. Recall $$Recall = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Negative\ (FN)} \quad (3)$$

d. F1-Score $$F1 - Score = 2.\ \frac{\text{Presisi . Recall}}{\text{Presisi + Recall}} \quad (4)$$

4. RESULTS AND DISCUSSION

An epoch is a complete cycle in the neural network training process, where the entire dataset is processed from start to finish. However, running training in a single epoch for large datasets tends to be inefficient and heavily burdens computing resources. As a solution, the dataset needs to be divided into smaller segments called batch sizes to improve data processing efficiency [19].

This study used two architectures, MobileNetV2 and EfficientNetB0, to classify brain tumor types. However, before using the CNN architecture, the researchers tried their own model. Testing was carried out by varying the number of epochs by 30 to compare the classification results for four types of brain tumors. In this study, the classification process was performed using 516 images divided into training and validation data. The next step was to train the brain tumor disease images to fit the model. Figures

4, 5, and 6 show the model generator fit results for each architecture. From epoch 1 to 30, there was a trend of increasing accuracy for both training and validation data.

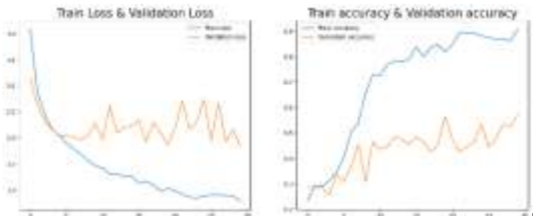


Figure 4. Graph of Training and Validation Data Accuracy Values of the Own Model

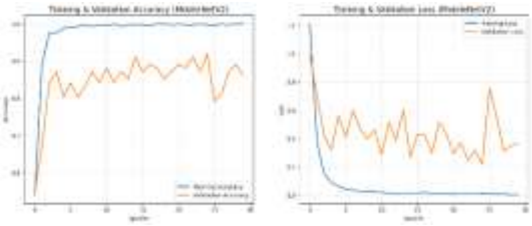


Figure 5. Graph of Training and Validation Data Accuracy Values of the MobileNetV2 Architecture

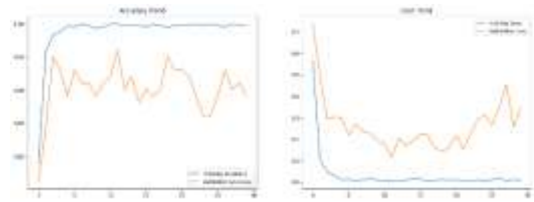


Figure 6. Graph of Training and Validation Data Accuracy Values of the EfficientNetB0 Architecture

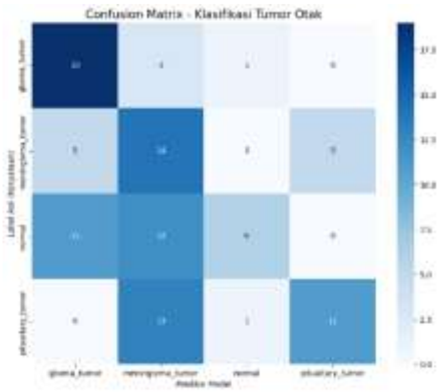
The best results for training, validation, and testing data for each model architecture from epochs 1 to 30 can be seen in Table 1.

Table 1. Summary of Model Results

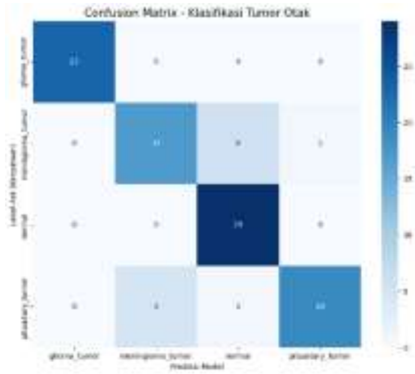
Architecture	Loss	Val Loss	Accuracy	Val Acc
Own Model	1.0022	2.1790	0.6197	0.4752
MobileNetV2	0.0492	0.6582	0.8886	0.8738
EfficientNetB0	0.0331	0.4963	0.9688	0.9481

The table 1. shows the performance comparison results between the three model architectures, where EfficientNetB0 proved to be the most superior model with the highest accuracy rate reaching 96.88% on the training data and 94.81% on the validation data. In second place, MobileNetV2 showed quite competitive performance with a validation accuracy of 87.38%, while the Own Model had the lowest performance with a validation accuracy of only 47.52%. The low performance of the Own Model accompanied by a very high Validation Loss value (2.1790) indicates an overfitting problem, in contrast to EfficientNetB0 which performed very stably with the lowest loss value (0.0331). Overall, these data conclude that the use of prestressed architectures such as EfficientNetB0 is much more effective and accurate in classifying data compared to other architectures in this test.

The confusion matrix is usually used to assess the effectiveness of a testing model on a dataset [20]. The results of the confusion matrix for each architectural model in this study can be seen in Figure 7.



(a)



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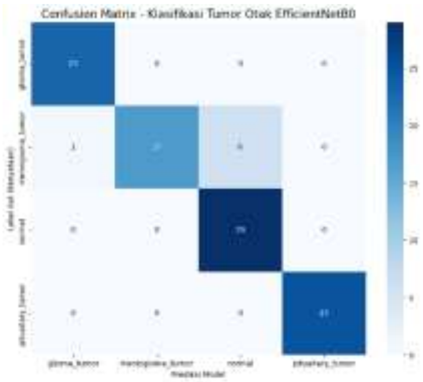

(c)

Figure 7. (a) Confusion Matrix My Own Model; (b) Confusion Matrix MobileNetV2; (c) Confusion Matrix EfficientNetB0

5. CONCLUSION

Based on the training, validation, and testing of the model implemented on a dataset containing 516 brain tumor images, it can be concluded that this study yielded good results. The best results were obtained using the EfficientNetB0 architecture, with a training accuracy of 96.88% and a validation accuracy of 94.81%. This study also demonstrated that careful selection and fine-tuning of model parameters can significantly improve the accuracy of CNN models in complex classification tasks.

This study also demonstrated that the EfficientNetB0 architecture is the most optimal model for classifying brain tumor types compared to the baseline model and MobileNetV2. Although MobileNetV2 has a large network depth, EfficientNetB0 outperforms it thanks to a combined scaling technique that balances network depth, width, and resolution proportionally. The main advantage of EfficientNetB0 is seen in its precision and recall values, which reached 0.97, indicating a very minimal risk of misdiagnosis (false negatives or false positives). This is particularly important in the medical field, where accurate tumor identification (glioma, meningioma, pituitary gland) significantly determines surgical procedures or patient therapy.
The main drawbacks of this study lie in the low performance of the custom model, which suffered from severe overfitting, as well as the accuracy gap with the pre-trained model, indicating that the regularization strategy still has room for improvement. Furthermore, this study did not explore the transparency of the model's decisions through visualization of tumor areas. Therefore, recommendations for future research include the application of more diverse data augmentation techniques or the use of Generative Adversarial Networks (GANs) to enrich the dataset, automatically optimize hyperparameters, and integrate explainable AI (XAI) methods such as Grad-CAM to enable visual verification of medical classification results by experts.

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