

Optimizing Brain Tumor Detection from MRI Images Through Combined VGG16 and ResNet50V2 Models with Batch Normalization

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ABSTRACT

Brain tumors are one of the most critical and life-threatening health conditions requiring rapid and accurate diagnostic support. Early detection plays a crucial role in determining appropriate medical interventions and improving patient survival rates. With advances in artificial intelligence, particularly computer vision, medical image transmission has emerged as a promising field to address the challenges of manual diagnosis, which is often time-consuming and prone to human error. Magnetic resonance imaging (MRI) is widely used in brain imaging due to its ability to provide detailed structural information, making it an ideal modality for tumor detection and classification.

This study employs a Convolutional Neural Network (CNN)-based approach that integrates two deep learning architectures: VGG16 and ResNet50V2, using batch normalization to improve feature extraction and reduce overfitting. Evaluation experiments were conducted on an MRI dataset of 1,311 brain tumor MRI images classified into pituitary, notoma, meningioma, and glioma classes. The aim of this study was to develop a fast, accurate, and efficient method for detecting brain tumors. The results show that the proposed hybrid architecture achieves 98% accuracy, outperforming each pretrained model when applied separately.

This study demonstrates that combining multiple CNN architectures with batch normalization can significantly improve the precision and accuracy of brain tumor detection. This approach has the potential to become a valuable diagnostic tool for radiologists, enabling faster and more accurate clinical decision-making. Furthermore, the application of such deep learning models in medical practice could contribute to reducing diagnostic errors and improving patient care in the long term.

Keywords: Brain Tumor Detection, Convolutional Neural Network, VGG16, ResNet50V2, Batch Normalization, Magnetic Resonance Imaging

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INTRODUCTION

Brain tumors are serious diseases that, despite being relatively rare, have a significant impact on morbidity, mortality, and the burden on global health systems. In 2019, approximately 348,000 new cases of brain cancer were recorded globally and 246,000 related deaths, indicating a high mortality rate from this disease (Ilic I, 2023). Globally, the age-standardized incidence rate (ASIR) is estimated at 4–5 per 100,000 people per year, with a nearly comparable mortality rate (Sung H, 2021).

In Indonesia and other developing countries, reported data tends to be incomplete. However, as an illustration, in the United States, approximately 23,890 new cases of brain tumors are reported annually, with a prevalence rate of 8–10 per 100,000 people. In Indonesia, there are 250 cases of brain tumors affecting both adults and infants (A.S. Febrianti, 2020). This suggests that the actual number of cases is likely higher due to limited access to healthcare and suboptimal record-

keeping. Early detection of brain tumors is critical for improving patient prognosis. Neurologists and neurosurgeons emphasize that earlier diagnosis and intervention can significantly increase the chances of survival and improve patients' quality of life (Gull S, 2021). However, manual diagnosis based on Magnetic Resonance Imaging (MRI) is time consuming and prone to inter-rater variability or human error. In recent years, deep learning, especially Convolutional Neural Networks (CNN) (Disci, 2025) (WongY, 2025), has demonstrated remarkable capabilities in automating the detection and classification of brain tumors using MRI images (Dorfner, F.J, 2025). Several studies have reported very high classification accuracy using multi-layer CNN models (Sultana, 2020) (Celik, F., 2024) specifically achieving 98.52% accuracy in brain tumor classification Frontiers (Mohamed Musthafa M, 2024).

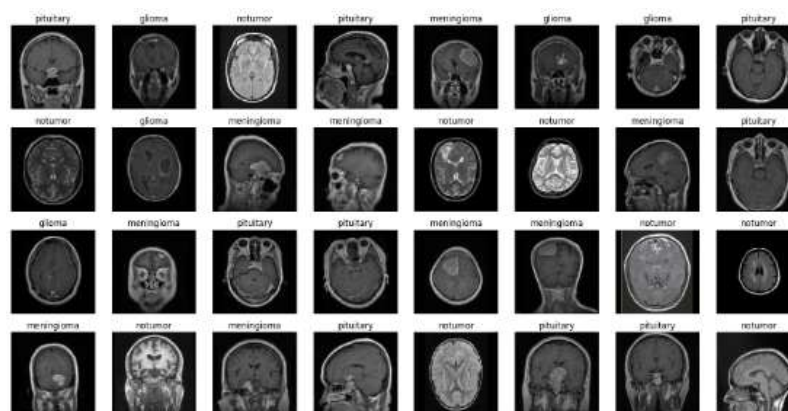
Fully CNN and transfer learning-based models such as GoogleNet achieved classification accuracy of up to 98.8% on the BRATS2020 dataset (Gull S, 2021). Other studies have shown that VGG-16 is capable of achieving accuracy of around 96%, while ResNet-50 is around 89% (Khan HA, 2020). Although these results are very promising, the main challenges that remain are overfitting due to relatively small or imbalanced datasets, model complexity that hinders processing efficiency and integration into clinical workflows, and the need to improve generalizability across various datasets and imaging conditions (Md. Monirul Islam, 2025) (Mienye, I. D, 2025). To address these challenges, this study proposes an innovative approach in the form of a hybrid CNN model (Akshay Bhuvaneswari Ramakrishnan, 2024) that combines the strengths of the VGG16 and ResNet50V2 architectures (A G Balamurugan, 2025), and uses batch normalization to improve training stability, feature extraction, while reducing overfitting. The evaluation was conducted on a brain MRI dataset of 1,311 images consisting of four classes: pituitary, no tumor, meningioma, and glioma. The results show an accuracy of 95.87%, which significantly exceeds the performance of each model when used separately.

Thus, this approach not only has the potential to accelerate and improve the accuracy of brain tumor detection, but also opens up opportunities for the integration of Artificial Intelligence-based diagnostic systems as effective, efficient, and reliable clinical tools.

METHOD

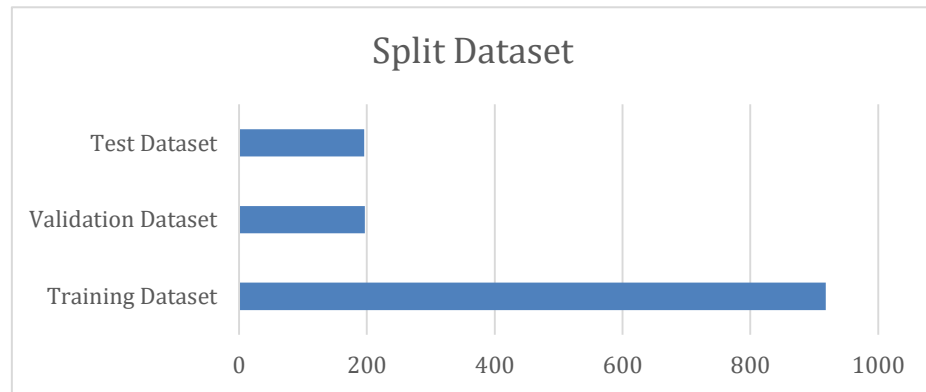
This research is a quantitative experimental study with a computational experiment approach that aims to design, implement, and evaluate a hybrid Convolutional Neural Network (CNN) model in detecting and classifying brain tumors in Magnetic Resonance Imaging (MRI) images. The dataset used consists of 1,311 brain MRI images divided into four classes: pituitary tumor, no tumor, meningioma, and glioma.

Figure 1. Brain Tumor MRI Image Dataset



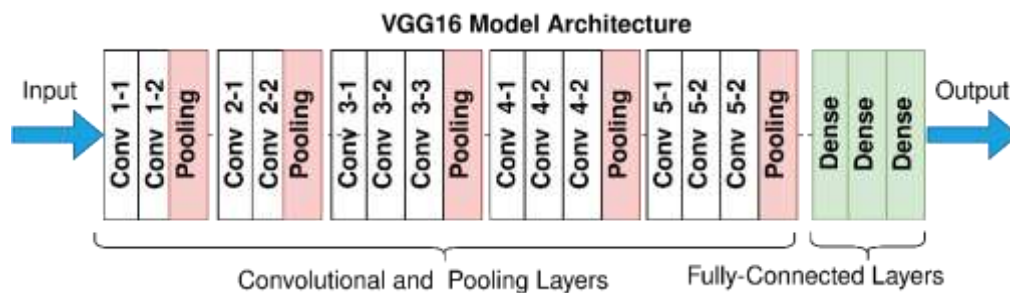
The data was then separated into training data (70%), validation data (15%), and test data (15%) to ensure the independence of the evaluation results.

Figure 2. Split Dataset



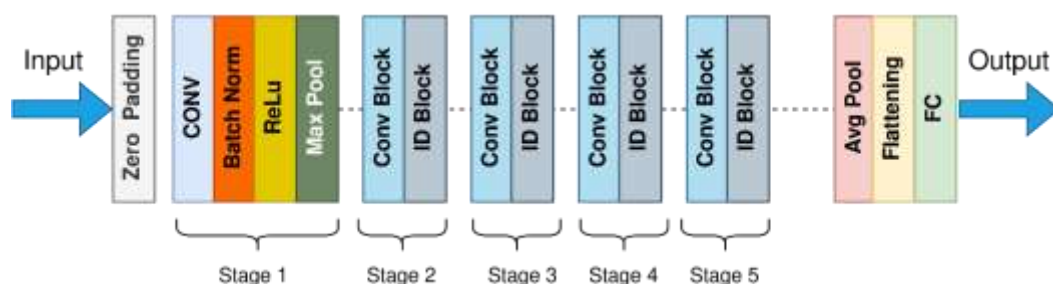
The data preprocessing stage is carried out by normalizing pixel intensities to the $[0,1]$ range to accelerate convergence, as well as resizing the image to a size of 256×256 pixels to suit the needs of the VGG16 and ResNet50V2 architectures. To increase variation and reduce the risk of overfitting, data augmentation is also performed in the form of rotation, flipping, zooming, and shifting.

Figure 3. VGG16 Architecture



The model architecture integrates two pre-trained models: VGG16 as a feature extractor for basic spatial patterns and ResNet50V2 for deeper feature extraction utilizing residual connections. Batch normalization is added to certain layers to improve training stability, accelerate convergence, and reduce overfitting.

Figure 4. ResNet50V2 Architecture with BatchNorm



The feature extraction results from both models are combined through a concatenation layer, then continued with a fully connected layer measuring 256 neurons with ReLU activation, followed by a dropout of 0.5 for regularization, and an output layer measuring 4 neurons with Softmax activation as a multi-class classification.

Model training was performed using the Adam optimizer with an initial learning rate of 0.0001, a batch size of 32, and a maximum number of epochs of 50, with early stopping based on the validation loss. The loss function used was categorical cross-entropy, in accordance with the nature of multi-class classification. Performance evaluation was performed on independent test data

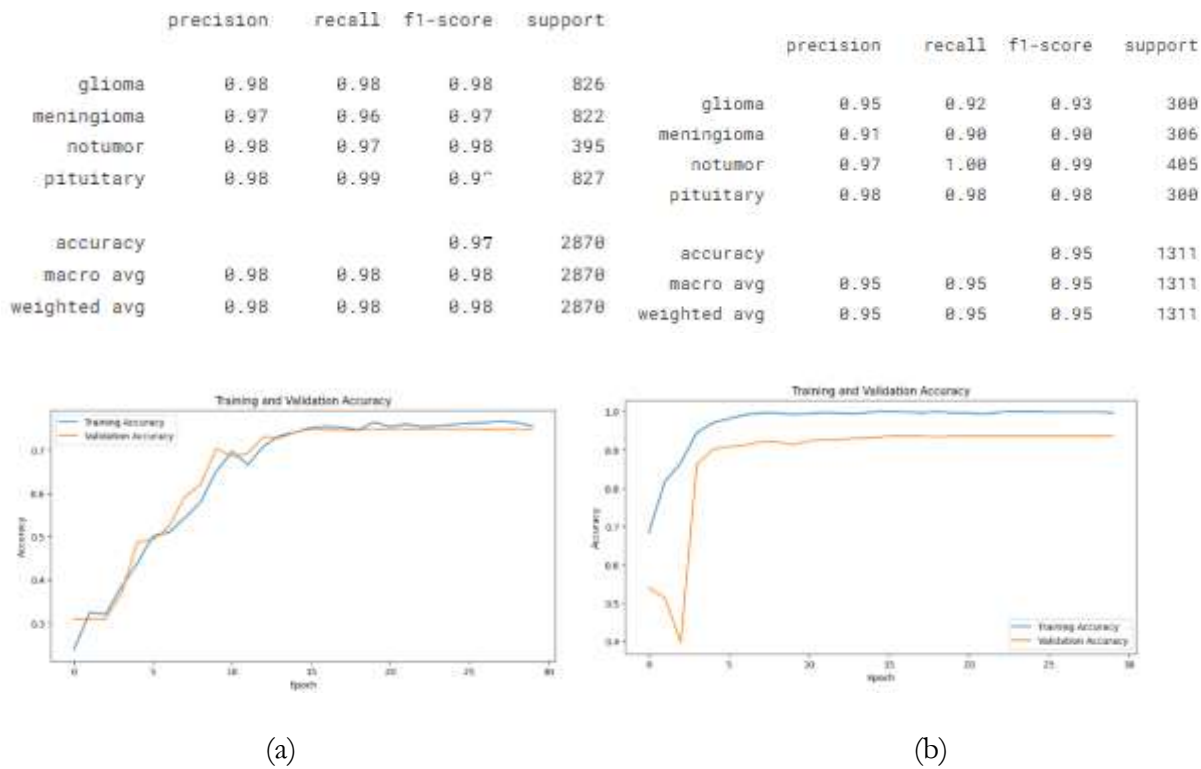
using metrics such as accuracy, precision, recall, and F1-score, as well as confusion matrix analysis to determine the classification distribution of each class.

The implementation was carried out using the Python programming language with the TensorFlow and Keras frameworks, and utilized NVIDIA GPUs to accelerate the training process. The performance of the hybrid model was then compared with the performance of the single VGG16 and ResNet50V2 models to determine the effectiveness of the proposed combined approach in improving the accuracy and generalization of brain tumor detection.

FINDING AND DISCUSSION

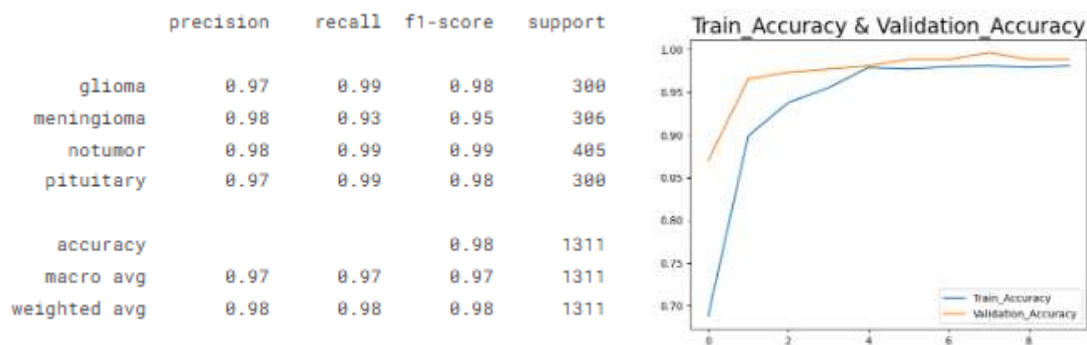
This study produced three different models that were tested in the process of classifying brain tumors from MRI images: a VGG16-based model, a ResNet50V2-based model, and a hybrid model that combines both architectures with the addition of batch normalization. The experimental results showed that the VGG16 model provided an accuracy of 97.711% and the ResNet50V2 model produced an accuracy of 95%, as shown in Figure 5.

Figure 4. Training results (a) using VGG16 architecture and (b) ResNet50v2



Seeing the excellent accuracy results of both architectures, the next step is to combine the two architectures in the hope of increasing accuracy. So, by experimenting with the combination of the two models with additional batch normalization, it was able to improve performance to reach 98% accuracy, which is the highest achievement in this study. This finding shows that the CNN architecture merging strategy not only improves training stability but also strengthens the model's ability to extract important features from brain MRI images.

Figure 5. Training results using VGG16 and ResNet50v2 architectures



Upon closer inspection, VGG16 demonstrates relatively high performance because its architecture is designed with moderate depth and simple convolution patterns that are effective in extracting basic spatial features. This makes VGG16 superior in detecting common patterns found in MRI images. In contrast, ResNet50V2, which has a more complex architecture with a residual connection mechanism, is essentially better suited for larger datasets, as it is capable of learning deeper and more complex features. However, on a relatively limited dataset like the one used in this study (1,311 images), ResNet50V2 tends to face the risk of overfitting, resulting in lower accuracy than VGG16. Therefore, although ResNet50V2 is very powerful theoretically, its application on a limited dataset has not been able to outperform VGG16.

The weaknesses of each individual model can be addressed by building a hybrid model that combines VGG16 and ResNet50V2, coupled with batch normalization in its architecture. Batch normalization plays a crucial role in normalizing the input distribution across each network layer, accelerating the convergence process, and reducing the internal covariate shift that often occurs in deep networks. Consequently, model training becomes more stable and accuracy can be improved. In this study, the application of batch normalization was shown to significantly increase accuracy by up to 98%. This demonstrates that the combination of a CNN architecture with additional regularization techniques can produce a more robust and reliable model for automatically detecting brain tumors.

No	Architecture	Loss	Accuracy
	VGG16	0,556	0,97
	ResNet50V2	0,613	0,95
	VGG16 + ResNet50V2	0,471	0,98

Viewing Accuracy based on evaluation accuracy is also done by looking at the accuracy, precision, recall, F1-score metrics, as well as confusion matrix analysis to see the classification distribution of each class.

Figure 4. Confusion Matrix Train Dataset and Test Dataset



In terms of implications, the results of this study have great potential for implementation as a clinical decision support system in radiology. The proposed model is capable of automatically detecting brain tumors with a high degree of accuracy, thus assisting radiologists in accelerating the diagnostic process while reducing the risk of human error. However, there are several limitations that should be noted. The dataset used is relatively small and comes from a limited single source, so the model's generalizability to a broader patient population still needs to be tested. For future research, it is recommended to use a larger, more diverse dataset that covers a more complex variety of clinical conditions. Furthermore, the application of other CNN method approaches is also important to make the model's prediction results more transparent and easily understood by medical professionals, thereby increasing the level of trust in this AI-based system.

CONCLUSIONS

This study demonstrates that the use of a Convolutional Neural Network (CNN) model can provide significant results in the detection and classification of brain tumors from MRI images. The VGG16 model achieved an accuracy of 97.711%, while ResNet50V2 achieved an accuracy of 95%. The combination of the two architectures with the addition of batch normalization was shown to increase performance up to 98%, indicating that the hybrid approach is more effective than using a single model. The integration of the two CNN architectures and the application of normalization techniques successfully reduced the risk of overfitting, strengthened feature extraction, and improved model training stability.

These results confirm that the CNN model integration strategy can be a potential solution in the development of medical decision support systems, particularly to accelerate and improve the accuracy of radiological diagnoses. With high accuracy, this model has the potential to assist medical personnel in making faster and more precise clinical decisions, and contribute to reducing diagnostic errors. However, this study still has shortcomings in the classification, as seen in the Loss Evaluation figures due to the dataset that is still unclear, resulting in shortcomings during the training process. For further development, this study suggests several things that can be the focus of future research. First, the use of larger, more diverse datasets sourced from various medical institutions is essential for the developed model to have better generalization capabilities across different patient populations. Second, the integration of more complex data augmentation methods can be considered to overcome the limited amount of data and increase the model's resilience to MRI image variations. Third, the application of other CNN method approaches such as EfficientNetV2 or VGG19 to improve model predictions, so that the classification results can be more easily understood and accepted by medical personnel.

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