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Deep Learning-Based Brain Tumor Classification using Transfer Learning

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Abstract This study explores enhancing the accuracy of diagnosing and classifying brain tumors through the utilization of transfer learning and fine-tuning using the ResNet50V2 model. While the basic CNN model achieved an accuracy of 95%, employing transfer learning with the ResNet50V2 model increased it to 97%. Subsequent fine-tuning further elevated the accuracy to an impressive 99.5%. Verification of the model's proper functionality was confirmed by executing it through a GUI-based program.

• Key Words : Deep Learning, CNN, Transfer Learning,, Fine-Tuning, ResNet

Ⅰ. Introduction

The exact cause of brain tumors has yet to be fully identified. Although some studies suggest that genetic factors may play a role, hereditary brain tumors are extremely rare. Malignant brain tumors, also known as brain cancer, grow rapidly and exhibit a high degree of infiltration into surrounding tissues. As a result, they tend to invade healthy brain tissue, making it difficult to distinguish tumor boundaries and complicating treatment [1]. Therefore, accurate and timely diagnosis is crucial for a favorable prognosis.

In this study, we investigate a brain tumor classification approach using convolutional neural networks (CNNs). To overcome the limitations identified in initial experiments, transfer learning is introduced to enhance model performance. We also present detailed experiments and results demonstrating how transfer learning and fine-tuning techniques were applied to address the shortcomings of the initial CNN model.

Ⅱ. Related Work

2.1 Computer-Aided Diagnosis (CAD) Systems

Currently, CAD is primarily utilized under the narrower concept of Computer-Aided Detection, and has been implemented in various commercial applications. One of the main advantages of CAD is that it provides a second opinion to medical professionals interpreting images and serves as a form of double reading, thereby helping reduce diagnostic errors.

Furthermore, CAD offers objectivity by ensuring the reproducibility of diagnostic results. As such, it minimizes the influence of subjective judgment and helps maintain consistency in medical image interpretation [2].

2.2 Deep Learning-Based Medical Services

In recent years, there has been rapid global progress in the research and development of medical services and support systems powered by deep learning.

In Korea, the company DeepBio developed an AI-based software called DeepDx-Prostate Pro in 2021 to assist in determining the severity of prostate cancer. This software received approval from the Korean Ministry of Food and Drug Safety and is currently being considered for overseas expansion in collaboration with prestigious institutions such as Stanford University School of Medicine and the Dana-Farber Cancer Institute.

Another Korean company, Coreline Soft, developed a solution named AVIEW LCS (Lung Cancer Screening) using AI algorithms to detect potentially cancerous pulmonary nodules and polyps. Clinical trials conducted at Asan Medical Center in Seoul demonstrated a patient-level detection sensitivity of approximately 97%.

Additionally, the company JLK Inspection introduced a software solution called JBS-01K, which analyzes chest X-ray images to highlight suspected nodules using color-coded indicators. This tool assists physicians in diagnosing lung nodules with improved efficiency [3].

Ⅲ. Brain Tumor Classification Using Transfer Learning

This study investigates brain tumor classification using deep learning-based transfer learning.

Figure 1 illustrates the architecture of the proposed neural network in this paper.

We employed the ResNet50V2 model to perform transfer learning and fine-tuning.

All experiments were conducted using a Ryzen 9 5900X CPU and an NVIDIA RTX 4070Ti GPU, within a development

environment consisting of Python 3.11.6 and PyCharm 2023.2.3.
The dataset used was a brain MRI dataset publicly available on Kaggle [4].

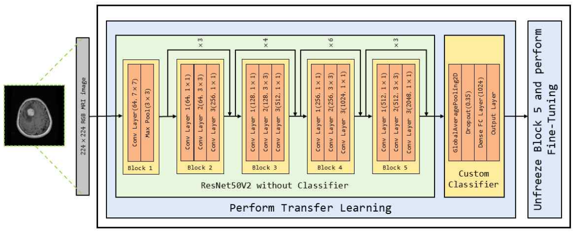

Figure 1. Overview of the Proposed Framework

Training the dataset using a conventional CNN model yielded a decent accuracy of 95%.
However, the confusion matrix revealed a critical issue: the model often misclassified brain tumors as normal tissue.
To address this problem, transfer learning was employed.
In this study, we evaluated 13 different transfer learning models on the dataset, and as shown in Figure 2, the ResNet50V2 model demonstrated the best performance and was thus selected for further experiments.

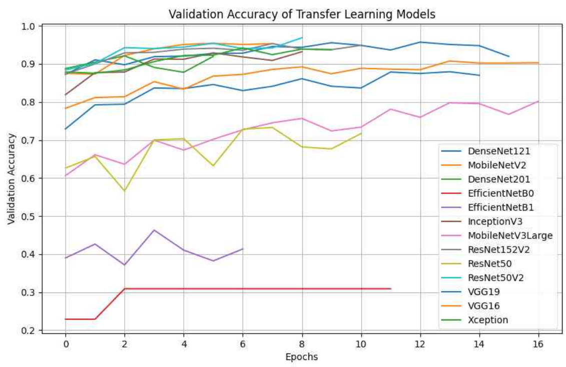

Figure 2. Performance Comparison of Transfer Learning Models

The ResNet50V2 model, pre-trained on 14 million images from the ImageNet dataset, has well-optimized weight parameters for extracting visual features and patterns.
Therefore, the pre-trained convolutional layers were loaded with frozen weights.
However, since the original classifier is designed to categorize inputs into 1,000 classes, it was not suitable for this task.
To address this, a custom classifier was implemented.
The custom head included Global Average Pooling 2D for flattening the feature maps, Dropout layers to prevent overfitting, and fully connected (FC) layers for final classification.

In convolutional neural networks, the higher layers combine basic features such as edges, lines, and colors—extracted from lower layers—to recognize more abstract patterns.
Based on this principle, we loaded the pre-trained model and unfroze only the highest-level layer, Block 5, for fine-tuning.
Given the strong performance of the pre-trained weights, the learning rate was set to a low value of 0.0001 to prevent performance degradation during fine-tuning.

Table 1 shows the evaluation metrics of the model after applying transfer learning and fine-tuning.
The model achieved precision, recall, and F1-score all above 0.99, with an accuracy of 99.54% and a loss of 1.6%, demonstrating superior performance compared to the baseline CNN model.

Table 1. Classification report

	Precision	Recall	F1-Score	Support
notumor	1.00	1.00	1.00	405
glioma	0.99	0.99	0.99	300
meningioma	0.99	0.99	0.99	306
piuitary	1.00	1.00	1.00	300
accuracy			0.9954	1311
loss			0.0160	1311

V. Conclusion

In this study, we proposed a brain tumor classification approach using transfer learning and fine-tuning with the ResNet50V2 model.
The model employing transfer learning and fine-tuning with ResNet50V2 outperformed a conventional CNN model in terms of accuracy and overall performance.
These results suggest that the proposed method can potentially contribute to the early diagnosis and treatment of brain tumor patients.

However, further validation is required to confirm its clinical applicability in real-world medical environments.
Future research should explore the use of various deep learning models and conduct comparative analyses to evaluate their effectiveness and suitability for medical image classification tasks.

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