Comparative Performance Analysis of Deep Learning Models for Brain Tumor Diagnosis Using MRI Images

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Abstract

This study evaluates the performance of deep learning models in diagnosing brain tumors from MRI images, using EfficientNet-B0, EfficientNet-B7, Swin Transformer, MaxViT, and ConvNeXt with the Brain Tumor MRI Dataset from Kaggle. Traditional MRI-based brain tumor diagnosis requires expert interpretation, making the process time-consuming and resource-intensive. Deep learning has shown potential in improving diagnostic accuracy and efficiency. The models were assessed based on accuracy, sensitivity, specificity, F1-score, and AUC-ROC, along with inference time and computational requirements. Results indicate that EfficientNet-B7 achieved the highest accuracy, followed by EfficientNet-B0, which provided strong performance with lower computational costs. Swin Transformer also demonstrated high accuracy, while MaxViT and ConvNeXt balanced speed and precision. These findings provide insights into the strengths and trade-offs of different models, which can be further utilized in related research and applications.

Introduction

Brain tumors significantly impact health and quality of life. While MRI is an effective diagnostic tool, interpretation requires expert radiologists, leading to delays and potential inconsistencies.

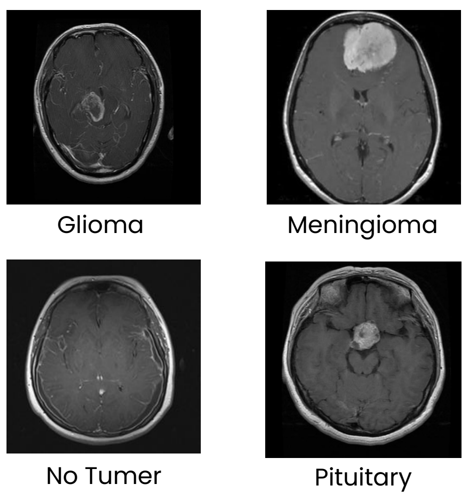
This study compares the performance of five machine learning models—EfficientNet-B0, EfficientNet-B7, Swin Transformer, MaxViT, and ConvNeXt—for brain tumor classification from MRI scans. By evaluating accuracy, inference time, and computational efficiency.

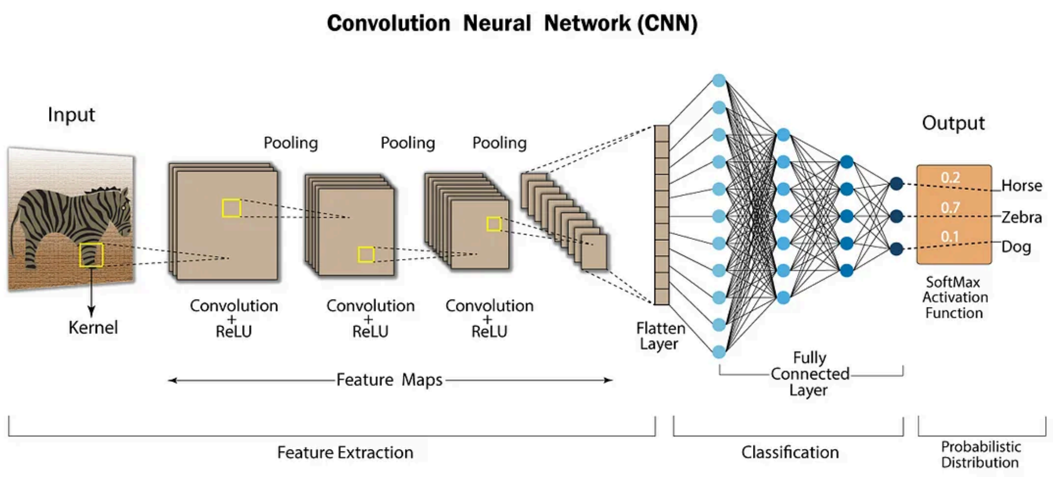
This research aims to identify the most suitable model for real-world medical applications, improving diagnostic speed and reducing workload for healthcare professionals.

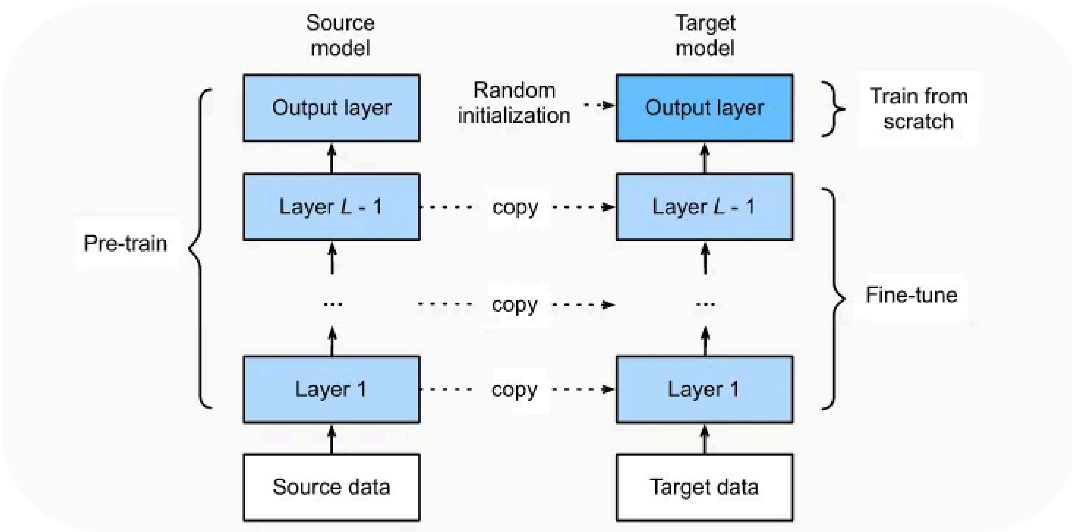
Objective

1. To compare the performance of various deep learning models for brain tumor detection from MRI images.
2. To analyze the feasibility of implementing these models in real world healthcare applications.

Method







- **Data Preparation**

1) Training Set (Total : 5,712 Pictures)
- Glioma Tumor : 1,321 Pictures
- Meningioma Tumor : 1,339 Pictures
- No Tumor : 1,595 Pictures
- Pituitary Tumor : 1,457 Pictures

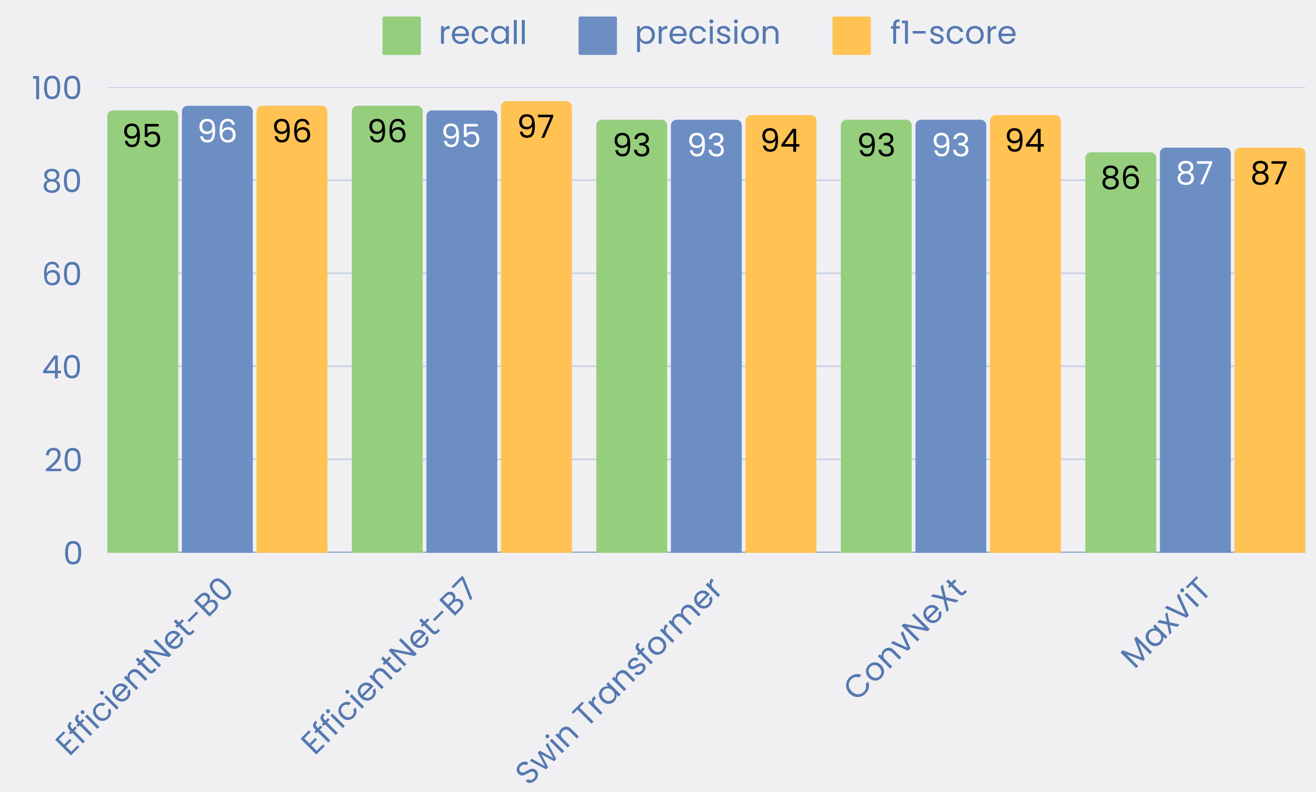
2) Testing Set (Total : 1311 Pictures)
- Glioma Tumor : 300 Pictures
- Meningioma Tumor : 306 Pictures
- No Tumor : 405 Pictures
- Pituitary Tumor : 300 Pictures

- **Model Selection**
  - Modernity : Models developed between 2019–2024, leveraging state-of-the-art architectures.
  - Number of Parameters : Models ranging from ~5M to ~120M parameters, ensuring compatibility with hardware constraints (8–16GB GPU).
  - Image-Specific Architecture : Combination of CNN-based models (EfficientNet, ConvNeXt) and Transformer-based models (Swin Transformer, MaxViT).
  - Accuracy : Models achieving accuracy between 85.2% and 92.3%, ensuring reliable brain tumor classification.

- **Model Adaptation & Deployment**

Data Preprocessing : MRI images were resized to 224×224 pixels, normalized, and split into training (81.34%) and testing (18.66%) sets to ensure a balanced dataset for model learning.
Model Fine-Tuning : Pre-trained deep learning models (EfficientNet, Swin Transformer, MaxViT, and ConvNeXt) were adapted by modifying the final classification layer to support four tumor classes, enabling them to specialize in brain tumor detection.
Optimization & Training : The models were fine-tuned using Cross-Entropy Loss and Adam Optimizer (LR=0.001), with training conducted for up to 20 epochs while incorporating Early Stopping to prevent overfitting.
Evaluation & Deployment : Performance was evaluated on unseen MRI images using Accuracy, Precision, Recall, and F1-Score, ensuring the model's reliability before deployment in real-world applications.

Result



Conclusion

This study compares the performance of deep learning models in diagnosing brain tumors from MRI images using EfficientNet-B0, EfficientNet-B7, Swin Transformer, MaxViT, and ConvNeXt, based on the Brain Tumor MRI Dataset from Kaggle. Traditional MRI-based brain tumor diagnosis requires expert interpretation, which can be time-consuming and resource-intensive. Deep learning offers a way to improve both accuracy and efficiency in this process.

The models were evaluated in terms of accuracy, sensitivity, specificity, F1-score, and AUC-ROC, as well as inference time and computational requirements. The results show that EfficientNet-B7 had the highest accuracy, followed by EfficientNet-B0, which performed well while using fewer resources. Swin Transformer also delivered strong accuracy, while MaxViT and ConvNeXt provided a balance between speed and precision.

These findings help us understand how different models perform and can be useful for future research or practical applications in medical imaging.