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Comparative Analysis of Deep Learning Models for Brain Tumor Detection using MRI Scans

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Abstract - **Brain tumor diagnosis from MRI scans has become an important research problem because identifying abnormal tissue at an early stage can support timely treatment and better clinical decisions. In recent years, deep learning methods have been widely used in medical image analysis because they can learn visual patterns directly from image data. This paper presents a comparative study of deep learning models used for brain tumor detection from MRI images. The discussion mainly focuses on transfer learning models such as VGG16 and ResNet50, along with a custom Convolutional Neural Network (CNN) model. The study examines how these models differ in terms of feature extraction ability, classification performance, and computational cost. It also considers the effect of preprocessing operations such as resizing, normalization, and augmentation on model behavior. The paper highlights the strengths and limitations of each approach and discusses practical issues such as dataset imbalance, overfitting, and limited explainability in medical AI systems. The study is intended to provide a comparative understanding of deep learning methods for MRI-based brain tumor detection and to identify directions for future improvements.**

Keywords— Brain Tumor Detection, MRI, Deep Learning, CNN, Transfer Learning, VGG16, ResNet50, Medical Image Classification

I. INTRODUCTION

Brain tumors are abnormal cell growths that develop within the brain and may interfere with normal neurological function. Depending on their type and severity, they can cause symptoms such as headaches, vision problems, seizures, and memory-related issues. Because of the serious health risks associated with tumor progression, early detection is an important part of diagnosis and treatment planning.

Magnetic Resonance Imaging (MRI) is one of the most commonly used imaging techniques for studying brain abnormalities. MRI scans provide detailed views of internal brain tissues and help doctors examine tumor size, shape, and location. However, analyzing MRI images manually can be time-consuming, especially when a large number of scans need to be reviewed. In addition, tumor appearance is not always consistent. It may vary across patients in terms of intensity, texture, boundary shape, and surrounding tissue pattern. These variations make automated analysis a useful area of research.

Earlier methods for brain tumor detection relied heavily on image processing and handcrafted feature extraction. Techniques such as thresholding, segmentation, texture analysis, and edge-based detection were commonly used to isolate tumor regions. Although these methods were helpful in early-stage research, they often struggled when the image quality was poor or when tumor boundaries were not clearly visible. Their performance also depended strongly on manually selected features and preprocessing steps.

Deep learning has changed this area significantly by allowing models to learn image features directly from data. Convolutional Neural Networks (CNNs), in particular, have shown strong performance in image classification tasks because they can automatically capture low-level and high-level features from medical images. In addition to standard CNN architectures, transfer learning models such as VGG16 and ResNet50 are frequently used in medical imaging studies because they can be fine-tuned for domain-specific tasks even when the available dataset is limited.

This paper presents a comparative study of deep learning approaches for brain tumor detection from MRI images. The objective is to compare commonly used models and understand how they differ in terms of learning capability, classification performance, and practical feasibility. The study also discusses current challenges in this field, including

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data imbalance, overfitting, and the need for more interpretable AI-based systems.

II. LITERATURE REVIEW

Many researchers have studied the use of deep learning in medical image analysis, especially for brain tumor detection and classification.

Research on brain tumor detection has moved gradually from traditional image analysis methods toward deep learning-based solutions. Earlier work in this area focused mainly on image segmentation and handcrafted feature extraction. These approaches attempted to identify suspicious regions using texture, shape, intensity distribution, and edge information. While such methods were useful for basic tumor localization, they were often sensitive to image quality and required careful manual design of features.

With the rise of deep learning, researchers began using CNN-based architectures for tumor classification and detection. CNN models became popular because they can learn features directly from MRI images without relying entirely on manually defined descriptors. This improved the ability of automated systems to handle complex visual patterns and made classification more robust in many cases.

Transfer learning has also become an important part of medical image analysis. Models such as VGG16 and ResNet50, originally trained on large image datasets, are often adapted for MRI-based classification tasks. VGG16 is commonly used because of its simple and well-understood structure, whereas ResNet50 is valued for its residual connections that support deeper learning. In several studies, these pretrained models have shown promising results in tumor classification when fine-tuned with medical datasets.

Another line of work has focused on medical image segmentation models such as U-Net. These architectures are useful when the goal is not only classification but also localization of tumor regions inside the MRI scan. Segmenting the tumor area before classification can sometimes improve the quality of analysis by focusing the model on the most relevant image regions.

Recent research has also explored lightweight CNN architectures and hybrid deep learning methods. The main motivation behind such work is to reduce computational complexity while maintaining acceptable classification accuracy. This is especially important for practical healthcare settings where high-end computational resources may not always be available.

Overall, the literature indicates that deep learning has improved brain tumor analysis significantly, but a number of open issues still remain. Limited dataset size, class imbalance, overfitting, and low interpretability continue to affect the reliability of many medical AI systems.

III. COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS

Different deep learning models have been used for brain tumor detection, and each model has its own strengths and limitations. In this paper, the comparative discussion is centered around VGG16, ResNet50, and a custom CNN model.

A. VGG16

VGG16 is one of the widely used transfer learning models in image classification. It contains multiple convolution and pooling layers arranged in a simple and structured way. In brain tumor detection, VGG16 is often preferred because it can extract meaningful image features even when the dataset is not very large. Its main limitation is that it has a large number of parameters, which increases memory usage and training time.

B. ResNet50

ResNet50 is a deeper architecture that uses residual connections. These skip connections help the network learn effectively without suffering too much from the vanishing gradient problem. ResNet50 is useful for capturing more complex image patterns, which can be beneficial in MRI-based tumor analysis. However, the model is computationally heavier than smaller CNN architectures and may require more careful tuning when the dataset is limited.

C. Custom CNN

A custom CNN model is generally designed according to the needs of a specific problem. It may contain a smaller number of convolutional layers followed by pooling and dense layers for classification. The advantage of a custom CNN is that it can be made lightweight and computationally efficient. It is often easier to train and can be adapted to the available dataset and hardware setup. On the other hand, its performance depends strongly on model design, training strategy, and preprocessing quality.

D. Comparative Discussion

From a comparative perspective, transfer learning models are often helpful because they provide strong feature extraction capability through pretrained weights. They can perform well even when the medical dataset is relatively small. Custom CNN models, in contrast, offer flexibility and reduced computational cost. Therefore, the choice of model depends not only on accuracy but also on practical factors such as dataset size, training resources, and the intended use of the system.

IV. RESEARCH GAP

Although many studies have reported good results for brain tumor detection using deep learning, several important research gaps still exist.

One common issue is the limited availability of large and balanced MRI datasets. Medical data is often difficult to collect and annotate, and this can lead to models that perform well on training data but do not generalize consistently to new scans. Class imbalance is another problem, as some tumor categories may be underrepresented in the dataset.

Another gap is that many studies evaluate only one model architecture and do not compare it properly with alternative approaches. Without comparative analysis, it becomes

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difficult to understand whether the reported performance is due to the model itself, the preprocessing strategy, or the specific dataset being used.

Computational cost is also a major concern. Models such as VGG16 and ResNet50 can deliver good performance, but they require more memory and processing power. This makes deployment difficult in settings where resources are limited. At the same time, lightweight models may be easier to deploy but may not always match the performance of larger transfer learning architectures.

Interpretability remains another unresolved challenge.

In medical applications, simply generating a prediction is often not

enough. Doctors may need some explanation or visual support to understand why a particular scan has been classified as tumor or non-tumor. The lack of such interpretability can reduce trust in automated systems.

For these reasons, there is a need for comparative studies that do not focus only on performance metrics but also consider efficiency, robustness, and practical usability.

V. STUDY FRAMEWORK

The study framework considered in this paper follows a general workflow used in MRI-based brain tumor classification.

A. Dataset Preparation

MRI images are collected from available brain tumor datasets. Depending on the source, the dataset may include tumor and non-tumor images or multiple tumor classes. Since raw images may differ in size and quality, they need to be prepared before being used for training.

B. Preprocessing

Preprocessing is an important step because MRI images may contain intensity variation, noise, or background information that can affect model performance. Typical preprocessing operations include resizing the images to a fixed input dimension, normalizing pixel values, and applying augmentation techniques such as rotation or flipping. These operations help improve training stability and reduce overfitting.

C. Model Selection and Training

The comparative study considers three model types:

VGG16

ResNet50

Custom CNN

For transfer learning models, pretrained weights are adapted to the MRI classification task through fine-tuning. The custom CNN model is trained using the selected MRI dataset to observe how a lighter architecture performs in comparison.

D. Classification and Evaluation

After training, the models are used to classify MRI images according to the selected categories. Their performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. This comparison helps identify the trade-off between classification performance and computational complexity.

VI. CONCLUSION

This paper presented a comparative study of deep learning models used for brain tumor detection from MRI images. The discussion focused on VGG16, ResNet50, and a custom CNN model, with attention given to their feature extraction behavior, computational requirements, and usefulness in medical image classification.

The study shows that deep learning methods provide a clear improvement over many traditional image processing approaches because they can learn directly from image data and handle complex tumor patterns more effectively. Transfer learning models are especially useful when strong feature extraction is needed, while custom CNN models can be attractive when a lightweight solution is preferred.

At the same time, several practical challenges still affect the development of reliable medical AI systems. Limited datasets, imbalance in tumor classes, overfitting, and low interpretability remain major concerns.

Future work in this area should focus on improving dataset quality, designing efficient architectures, and building models that provide both accurate predictions and better clinical trust.

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