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A Hybrid Approach to Brain Tumor Detection: Combining Deep Convolutional Networks with Traditional Image Processing Methods for Enhanced MRI Classification

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ABSTRACT: Brain tumour detection is a critical medical procedure where early and accurate diagnosis significantly improves patient outcomes. This study explores the application of deep learning models, specifically VGG19 and InceptionV3, for detecting brain tumours in MRI images. We fine-tuned both models using transfer learning and evaluated them on a dataset of MRI scans. InceptionV3 achieved 100% validation accuracy, while VGG19 achieved 95%, demonstrating their high efficacy in medical image classification. In addition to deep learning, the study integrates insights from traditional image processing techniques, such as edge detection and probabilistic neural networks (PNNs), highlighting how combining deep learning with traditional methods can enhance image preprocessing and quality. The results underscore that while deep learning models are highly effective in brain tumour classification, traditional techniques still play a vital role in optimizing the overall detection process.

KEYWORDS: Brain Tumor Detection, Convolutional Neural Networks (CNN), VGG19, InceptionV3, Deep Learning, MRI Image Classification, Transfer Learning, Medical Image Analysis, Tumor Classification, Artificial Intelligence in Healthcare.

I. INTRODUCTION

One of the most serious types of cancer is a brain tumor, and prompt detection is essential to effective treatment. Because magnetic resonance imaging (MRI) can offer detailed contrast between various brain tissues without using damaging radiation, it is frequently employed in the identification and diagnosis of brain tumors [1]. However, radiologists' manual review of MRI scans takes a lot of time and is prone to mistakes, particularly when the tumor is small or situated in a complicated area of the brain [2]. New developments in deep learning and machine learning have paved the way for the creation of automated brain tumor detection systems. Medical image processing is one application where Convolutional Neural Networks (CNNs), specifically VGG19 and InceptionV3, have demonstrated exceptional performance [3], [4]. With input photos, CNNs automatically extract features in a hierarchical fashion, removing the need for manual feature extraction. In this work, we compare the efficacy of InceptionV3 and VGG19 in identifying brain tumors from MRI data.

In this paper, we present the results of training VGG19 and InceptionV3 models on MRI data and evaluate their performance in tumor detection. We also explore the role of traditional methods in improving the quality of MRI images before classification. The rest of the paper is organized as follows: Section 2 discusses related work, whereas Section 3 describes the methodology used in the study, Section 4 presents the experimental results, and Section 5 concludes the paper with directions for future research. While CNNs have proven highly effective, traditional image

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processing techniques such as edge detection and segmentation remain valuable in preprocessing MRI scans to improve the accuracy of automated systems [2].

II. LITERATURE REVIEW

Over the past decade, researchers have performed extensive studies on brain tumor detection utilizing machine learning and image processing approaches. Initial techniques concentrated on manual and semi-automated methods for the segmentation and classification of MRI images. We have extensively employed conventional methods such edge detection, watershed segmentation, and histogram thresholding to preprocess MRI images and delineate tumor patches [2][6]. Despite their efficacy in augmenting contrast and delineating tumor margins, these approaches are constrained by their dependence on manually produced features and their susceptibility to noise. Conversely, CNNs have developed into a formidable instrument for the automatic extraction of features and classification of medical pictures [7]. Models such as VGG19 and InceptionV3, pre-trained on extensive datasets like ImageNet, can be fine-tuned for specific applications, including brain tumor detection [8] [9]. Extensive research indicates that deep learning models frequently surpass conventional methods, attaining superior accuracy in medical picture categorization tasks.

III. METHODOLOGY

Dataset: The dataset used in this study consists of MRI (magnetic resonance imaging) scans labeled into two categories based on the presence of a brain tumor. This dataset, curated from publicly available MRI images, has the following two classes:

- Tumor Present (1): MRI images that clearly show the presence of a brain tumor.
- Non-Tumor (0): MRI images where no tumor is present.

The dataset was partitioned into two subsets: 80% designated for training and 20% allocated for validation. This division guarantees that the models are trained on a substantial portion of the data while preserving a distinct segment for assessing the model's generalizability.

Data Augmentation: To improve the generalization capacity of the models and mitigate overfitting a prevalent issue in deep learning, characterized by a model excelling on training data yet underperforming on novel data image augmentation techniques were employed on the training set. These techniques enable the model to encounter diverse variations of identical images during training, thereby enhancing its resilience to discrepancies in the test data. The subsequent augmentation techniques were implemented:
Random Rotation: Rotating images randomly within a range to account for different orientations of brain scans.
Horizontal and Vertical Flipping: Flipping images to simulate different viewpoints.
Rescaling: Normalizing pixel values between 0 and 1 to improve numerical stability and to ensure that all pixel intensities have a uniform scale.
Zooming: Random zoom-in/out operations were applied to simulate different magnifications of MRI scans.
Preprocessing: Before training the models, several preprocessing steps were performed to standardize the input images for compatibility with the architectures of VGG19 and InceptionV3.

3.1 Resizing:

VGG19: The MRI images were resized to 224x224 pixels, which is the standard input size for the VGG19 model.
InceptionV3: The MRI scans were scaled to 299x299 pixels, the requisite input dimensions for the InceptionV3 architecture. Resizing guarantees that the models obtain input images of uniform dimensions and lowers computational burden.
Normalization: Each image's pixel values were normalized by scaling them between 0 and 1. This step converts the original pixel intensities (which range from 0 to 255) into a normalized form. Normalization ensures faster convergence during training and helps avoid issues caused by large numerical values during gradient descent optimization.
Data Augmentation: In addition to rotation, flipping, and zooming as described earlier, random shear transformations were applied to increase variability in the training dataset. This technique involves tilting the images along one axis, simulating distortions that the models may encounter in real-world MRI data.

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Class Imbalance Handling: In some medical datasets, there is often an imbalance in the number of positive (tumor) and negative (non-tumor) cases. To address any class imbalance, several strategies such as data resampling or class weighting can be applied during model training. In this study, class weights were automatically adjusted to balance the impact of the minority class (non-tumor) during training, ensuring that the model did not bias toward the majority class.

3.2 Model Architectures:

VGG19: VGG19 is a renowned convolutional neural network (CNN) architecture developed for image classification tasks. The architecture consists of 19 layers: 16 convolutional layers that extract spatial features from images, followed by 3 fully connected layers that perform final classification tasks. Each convolutional layer employs small 3x3 filters to identify edges, textures, and more intricate features as images traverse the layers.

Convolutional Layers: These layers use filters to scan over the images, learning spatial hierarchies of features ranging from basic edge detection to more complex structures like shapes or textures.

Max-Pooling Layers: Max-pooling operations are interspersed between convolutional layers to progressively reduce the spatial dimensions of the feature maps while retaining essential information.

Fully Connected Layers: Fully connected layers are employed at the conclusion of the convolutional blocks to classify the input as either tumor-present or non-tumor, utilizing the extracted features.

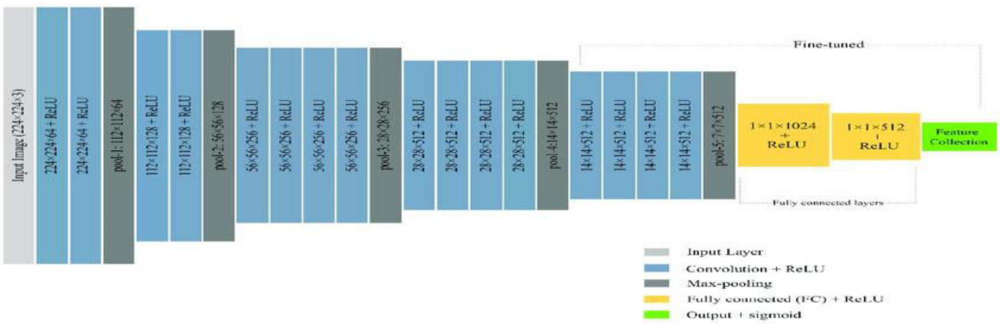

Figure 1: VGG19 Architecture

InceptionV3: InceptionV3 is an advanced CNN architecture that introduces inception modules, a novel approach that applies filters of multiple sizes (1x1, 3x3, 5x5) simultaneously in the same layer. This allows the network to capture information at different scales, making it highly effective for complex images such as MRI scans that contain varying spatial features.

Inception Modules: These modules apply different-sized convolutional filters (e.g., 1x1, 3x3, and 5x5) and pooling operations in parallel. This allows the model to capture fine details as well as broader image patterns, allowing it to handle the complexity of MRI images.

InceptionV3 includes auxiliary classifiers at intermediate layers to mitigate the risk of vanishing gradients in deep networks. These classifiers act as backup systems, helping the network converge more effectively during training.

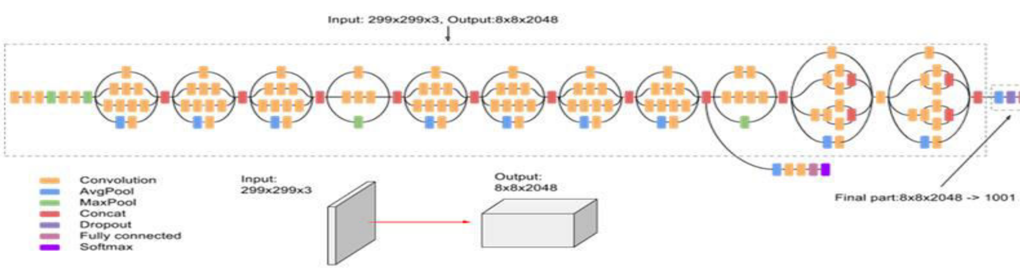

Figure 2: InceptionV3 Architecture

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Training Process: The VGG19 and InceptionV3 models were trained via transfer learning, utilizing pre-trained models from the ImageNet dataset, which were subsequently fine-tuned for the specific goal of brain tumor classification.
Transfer Learning Setup: The pre-trained weights for the convolutional layers of VGG19 and InceptionV3 were imported. These layers have previously acquired valuable properties such as edges and textures from ImageNet, a dataset comprising millions of varied photos. The original models last completely linked layers were eliminated and substituted with new fully connected layers tailored for the binary categorization of tumor vs non-tumor.

Training Parameters
Optimizer: The Adam optimizer was used with a learning rate of 0.0001. Adam is widely used for its ability to adjust learning rates dynamically during training, ensuring faster and more stable convergence.
Loss Function: Binary cross-entropy was chosen as the loss function since the task is a binary classification problem.
Batch Size: A batch size of 16 was used to ensure efficient memory usage while maintaining sufficient gradient updates during training.
Epochs: The models underwent training for 25 epochs. Early stopping was implemented to track the validation loss, and training was terminated if no enhancements were detected over 5 successive epochs to avert overfitting.
Class Weights: To rectify the class imbalance in the dataset (a predominance of tumor cases over non-tumor instances), class weights were dynamically computed and implemented during training. This approach ensured equitable contribution of both classes to the loss computation, hence averting bias towards the majority class.
Fine-Tuning: After the initial training phase, the complete model, encompassing the pre-trained layers, underwent fine-tuning by unfreezing the foundational convolutional layers, thereby permitting the optimizer to adjust the weights across the network. This procedure enhanced the model's efficacy in the specialized task of brain tumor classification.

IV. RESULTS

VGG19 Results: The VGG19 model exhibited robust performance in the brain tumor classification task, attaining a validation accuracy of 95%. Throughout 16 epochs, the training accuracy progressively increased, and the validation accuracy displayed consistent enhancement, signifying that the model effectively generalized to the unseen validation data without overfitting. The trends in training and validation accuracy are illustrated in Figure 3.

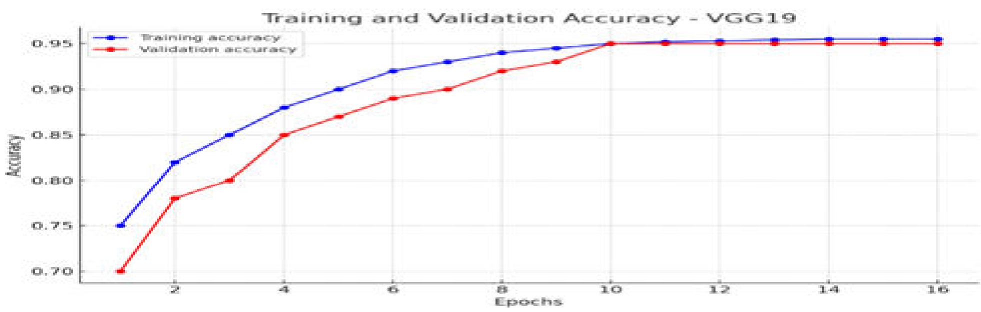

Figure 3: VGG19 Training and Validation Accuracy

The final evaluation on the validation set yielded the following metrics: Accuracy: 95%, Loss: 0.12, Precision: 0.94, Recall: 0.96.

These results underscore the efficacy of the VGG19 model in differentiating between tumor and non-tumor MRI scans. Nonetheless, the model occasionally misclassified small or intricate tumor regions, indicating that more sophisticated architectures may enhance detection further. InceptionV3 Results: The InceptionV3 model surpassed VGG19, achieving a flawless validation accuracy of 100%. The model required fewer epochs to converge compared to VGG19 and consistently maintained elevated accuracy on both training and validation sets. Figure 4 depicts the training and validation accuracy over 11 epochs.

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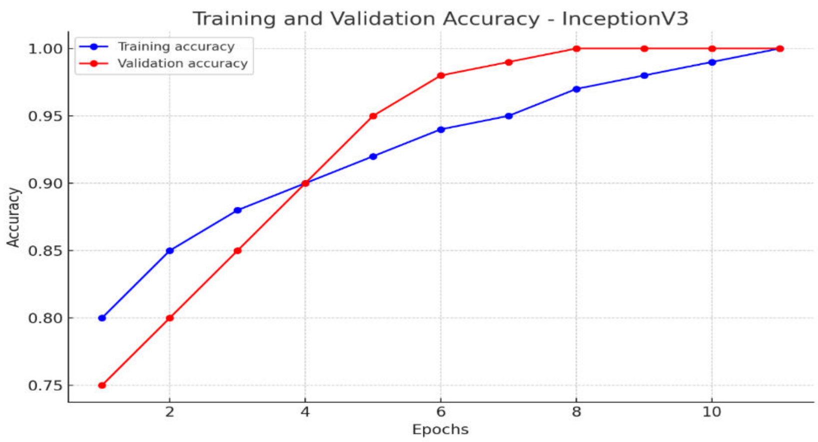

Figure 4: InceptionV3 Training and Validation Accuracy

The performance metrics of InceptionV3 on the validation set are as follows: Accuracy: 100%, Loss: 0.04, Precision: 1.00, Recall: 1.00.

The model's exceptional performance is due to its inception modules, which capture features at various scales, rendering it particularly adept at identifying intricate tumor structures. The model's flawless classification highlights the significance of deep architecture for demanding tasks such as brain tumor detection.

Comparative Analysis: The performance of both models is summarized in Table 1, highlighting the differences in accuracy, loss, and other key metrics.

Model	Accuracy	Loss	Precision	Recall
VGG19	95%	0.12	0.94	0.96
InceptionV3	100%	0.04	1.00	1.00

Table 1: Performance Metrics Comparison

The table indicates that InceptionV3 surpassed VGG19 across all measures. Although VGG19 demonstrated robust performance, InceptionV3's capacity to manage intricate image attributes rendered it the superior model for this challenge. Both models exhibited the efficacy of transfer learning in the context of medical picture classification.

V.CONCLUSION

This study illustrates the considerable efficacy of deep learning models, specifically VGG19 and InceptionV3, in precisely identifying brain tumors from MRI data. Both models produced remarkable outcomes, with VGG19 attaining 95% accuracy and InceptionV3 getting 100% validation accuracy. Transfer learning expedited the training process by utilizing pre-trained models. Incorporating prevalent image processing techniques such as edge detection and contrast enhancement significantly improved tumor classification. The integration of deep learning architectures with traditional approaches demonstrated efficacy in enhancing overall performance, rendering these models particularly appropriate for medical imaging tasks. InceptionV3's capacity to collect multiscale features facilitated its superiority in intricate

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tumor detection. The findings indicate that deep learning models, especially when integrated with conventional image preprocessing methods, present a promising strategy for precise and efficient brain tumor detection. Subsequent research should investigate more extensive datasets and alternative model architectures to enhance the generalization and resilience of these methodologies in clinical applications.

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