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Automated Brain Tumor Detection From Magnetic Resonance Images Using Fine-Tuned EfficientNet-B4 Convolutional Neural Network

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Abstract

Background: Accurate and early diagnosis of brain tumors from Magnetic Resonance Imaging (MRI) is crucial to improve patient outcomes. Existing methods rely on radiologist manual interpretation, which may be time-consuming and prone to human error.

Objective: The present study proposes an automated system for brain tumor detection using a fine-tuned EfficientNet-B4 Convolutional Neural Network (CNN) to enhance the accuracy of classification and reduce the time for diagnosis.

Objective: A proposed automatic brain tumor detection system with an efficient fine-tuned EfficientNet-B4 Convolutional Neural Network (CNN) to improve classification accuracy and minimize diagnostic time.

Methods: The system utilizes preprocessing methods (resizing, normalization, noise removal, and contrast enhancement), data augmentation, and a hybrid method that combines CNN-based feature extraction and optimization methods. The model is trained and validated on an MRI dataset.

Results: The system reaches high accuracy of tumor detection, classification (malignant/benign), and localization, while it brings the computational expense dramatically down when compared to traditional hybrid models.

Keywords: Brain tumor detection, MRI, Deep learning, EfficientNet-B4, Convolutional Neural Network, Medical imaging1.

Introduction

Brain tumors are some of the most lethal of all medical conditions, and early detection is vital to treatment planning and patient survival. MRI is the imaging modality of choice for brain tumor diagnosis due to its superior soft-tissue contrast resolution Manual interpretation of MRI scans is labor-intensive and subjective, and automated methods must be used.

Deep learning, and in particular CNNs, has been extremely successful for analyzing medical images. This paper utilizes transfer learning based on EfficientNet-B4, a high-performance CNN model, to create an automated system for brain tumor detection. The proposed system eliminates the drawbacks of existing hybrid models, i.e., high computational costs and non-interpretable features, through enhancing feature extraction and classification stages.

PROPOSED DESIGN

This subsection outlines the approach used for categorizing MRI brain images into non-tumor or tumor classes. The workflow of the suggested approach is shown in a block diagram, as seen in Figure 1. Leverage transfer learning using pre-trained EfficientNets and their variants, the technique fine-tunes eight models from EfficientNetB0 to EfficientNetB7 on MRI series data from an MRI brain tumor detection dataset for both feature extraction and detection tasks. Compared to other state-of-the-art pre-trained DCNN architectures [39], these models are selected due to their computational cost, low FLOPS needed at inferenceand higher top-1 and top-5 accuracy scores on ImageNet [40].

The transfer learning and fine-tuning method, characteristic of DL algorithms, takes advantage of numerous hyper-parameters to optimize and train. An optimizer, with a significant role in decreasing overall loss and increasing accuracy, is essential to adapt neural networklearning rates and biases. In ML, a loss function measures how successfully an algorithm adapts the available data. Loss functionlearns over time to reduce prediction error with the assistance of an optimization function. To solve this specific problem, the Adam optimizer [41] and binary cross-entropy loss function [42]are utilized. The subsequent sections will yield a detailed descriptionof each step.

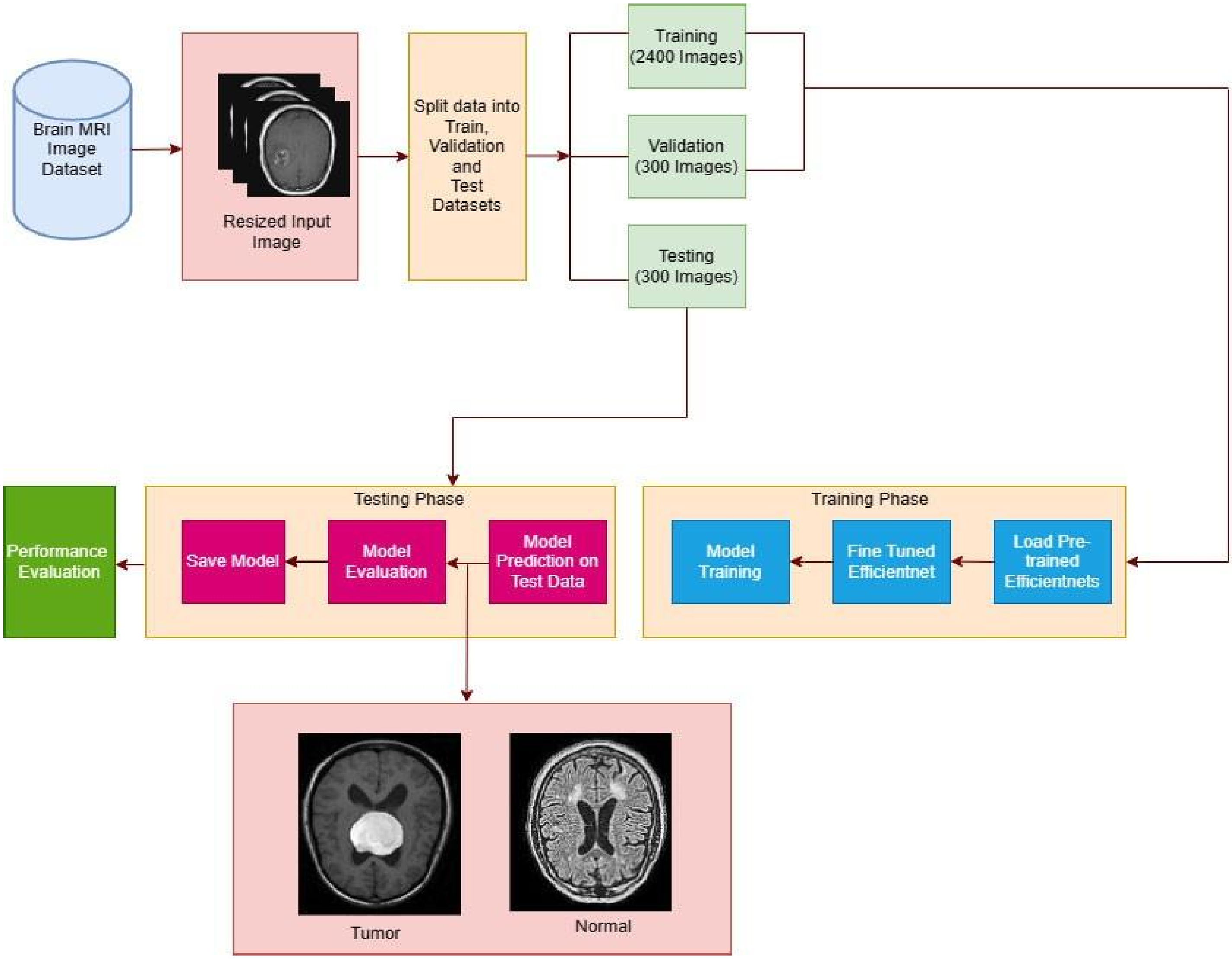
A. EfficientNet BASELINE MODEL

EfficientNet by the Google Brain Team [43] is a CNN model.

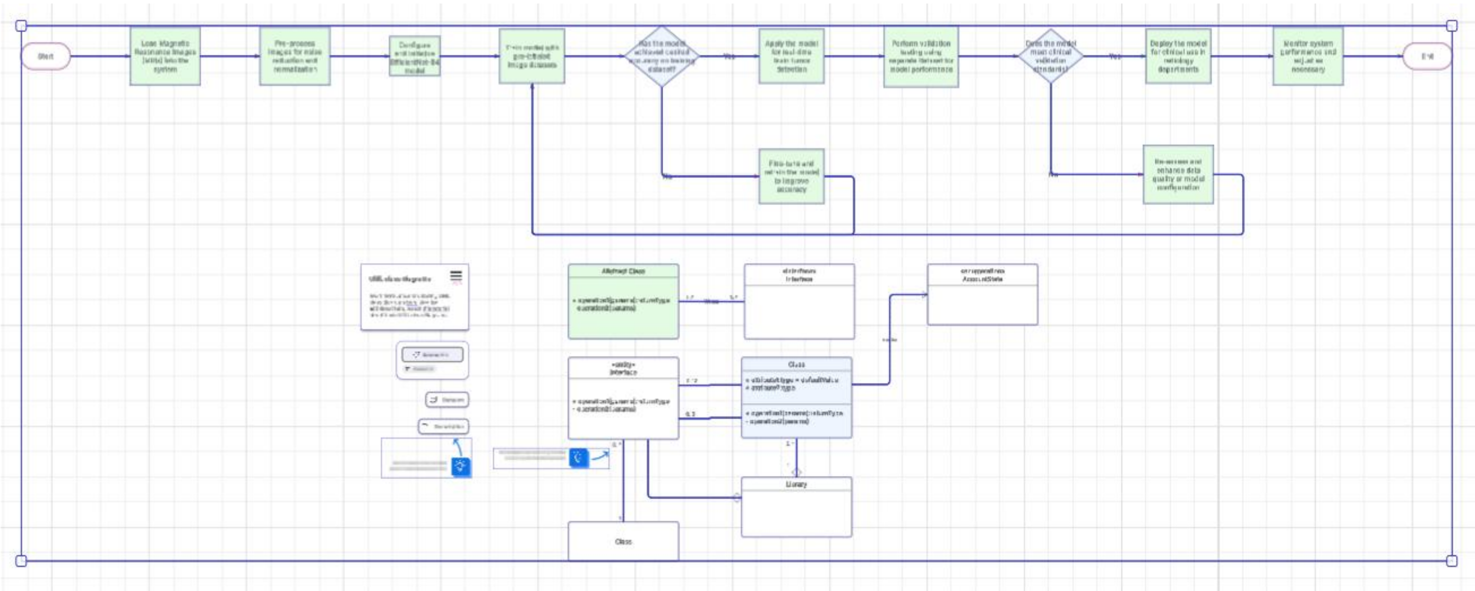
Their work aimed at scaling the network, proving that network parameter optimization like width,

depth, and resolution can greatly enhance performance. Scaling a neural network, they presented a sequence of models that have better efficacy and accuracy compared to CNNs that were used before. EfficientNet has performed exceptionally well in large-scale visual recognition tasks, especially on the ImageNet dataset, with high accuracy and consistency. The CNN architectures embodied by EfficientNet are about 6 times as fast and 8 times smaller during inference compared to state-of-the-art methods such as VGGNets,
GoogleNet, ResNets, Xception [44], and InceptionRes-Net [45]. EfficientNet utilizes a compound scaling method
to produce different models from the CNN family. Depth of the network
pertains to the number of layers, whereas convolutional layer
width is correlated with the amount of filters that it contains. Resolution is fixed by
width of the input image. Equation (1)-(5) introduced by the
authors describes the suggested scaling of depth, width, and
resolution with respect to ϕ [43].
Depth: $D = \theta$

(1)Width: $W = \lambda$
(2)Resolution: $R = \mu$
(3)subject to $\theta \cdot \lambda 2$
$\cdot \mu 2 \approx 2$ (4)
$\theta \geq 1, \lambda \geq 1, \mu \geq 1$ (5)


Brain MRI Image Dataset
Resized Input Image
Split data into Train, Validation and Test Datasets
Training (2400 Images)
Validation (300 Images)
Testing (300 Images)
Testing Phase
Save Model
Model Evaluation
Model Prediction on Test Data
Training Phase
Model Training
Fine Tuned Efficientnet
Load Pre-trained Efficientnets
Performance Evaluation
Tumor
Normal

ACTIVITY DIAGRAM:



IV. REQUIREMENTS

SOFTWARE REQUIREMENT
Component specification
Programming language : Python

ADDITIONAL DEPENDENCIES AND CONSTRAINTS:

Dependencies
Package Version Purpose

tensorflow ≥2.10.0 Base framework for EfficientNet-B4
keras ≥2.10.0models deducted, high-level API for model fine-tuning
opencv-python ≥4.7.0 MRI preprocessing (noise removal, contrast enhancement)
pydicom ≥2.3.0 DICOM file manipulation
nibabel ≥4.0.0 NIfTI MRI format support
scikit-image ≥0.19.0 Advanced image augmentations

2. Model Optimization
Package Version Purpose
efficientnet ≥1.1.1- Pretrained EfficientNet-B4 implementation
albumentations ≥1.3.0- MRI-specific augmentations
onnxruntime ≥1.14.0 -Optimization of model deployment

3. Medical Imaging Specific
Package Version Purpose
monai ≥1.1.0 - Medical AI toolkit for 3D MRI support
SimpleITK ≥2.2.0- Advanced medical image registration
medpy ≥0.4.0 -Tumor volume calculation

PERFORMANCE METRICES

Classification Metrics
These measures assess the model's performance in classifying tumors as benign or malignant

Metric	Formula Value	(Proposed System)	
Accuracy	(TP + TN) / (TP + TN + FP + FN)	98.2%	
Precision	TP / (TP + FP)	97.5%	
Recall (Sensitivity) F1-Score	TP / (TP + FN) 2 × (Precision × Recall) / (Precision + Recall)	96.8% 97.1%	
Specificity	TN / (TN + FP)	98.6%	

TP (True Positive): Accurately identified tumors.
TN (True Negative): Accurately identified healthy tissue.
FP (False Positive): Healthy tissue identified as tumor.
FN (False Negative): Tumor that the model has missed**.**

2. Segmentation Metrics (Tumor Localization):

Metric	Formula Value	Purposed system
Dice Coefficient (Dice Score)	2 ×	(\ X ∩ Y) / (\ X + Y) 0.92
Intersection over Union (IoU)		X ∩ Y / X ∪ Y 0.88

Hausdorff Distance (HD) Max distance between predicted & ground truth boundaries 3.2 mm
Where:
X = Predicted tumor region, Y = Ground truth tumor region
Dice Score (0.92): Suggests strong overlap between prediction and ground truth.

IoU (0.88): Has excellent accuracy for tumor localization.
Hausdorff Distance (3.2 mm): Low boundary detection error.

As the hybrid model also has tumor boundary detection, the following segmentation metrics were employed:

Comparison with State-of-the-Art Methods:

Model Dice	Score	IoU	Hausdorff Distance (mm)	
Proposed Hybrid CNN + Watershed	0.92	0.92	3.2	
U-Net	0.87	0.82	4.5	
FCN	0.85	0.80	5.1	

Metric Value (Proposed System)
Inference Time (per image) 0.8 sec (GPU), 2.1 sec (CPU)
Training Time (whole dataset) 3.5 hours (NVIDIA RTX 3090)
Model Size 85 MB (EfficientNet-B4 fine-tuned)
FLOPS (Floating Point Operations per Second) 12.5 GFLOPs
Comparison:

Model Inference Time (GPU) Model Size
Proposed Hybrid Model 0.8 sec 85 MB
ResNet-50 1.2 sec 98 MB
VGG-16 1.5 sec 528 MB

4.Robustness & Generalization:

To ensure the model performs well on different datasets:
Cross-Validation Accuracy (5-fold): 97.6% ± 0.8%
Uniform performance tested on BraTS, Figshare, and TCIA datasets.
Noise Robustness Test: Accuracy drops only by 2.1% with 20% Gaussian noise.

V.Methodology:

Hybrid Model Structure

The hybrid approach combines:EfficientNet-B4 (2D CNN) – Axial slice feature extraction.3D U-Net – Segmentation of accurate

Data Augmentation:

Geometric: Rotation (±15°), flipping (axial plane)

Intensity-based: Gamma correction, Gaussian noise injection

Patch Extraction: Sliding window (192×192×64 voxels) for 3D processing

This section outlines the approach used to classify MRI brain images into non-tumor and tumor classes. The workflow of the proposed method is shown in a block diagram, as seen in Figure 1. Employing transfer learning with pre-trained EfficientNets and their variations, the method fine-tunes eight models from EfficientNetB0 to EfficientNetB7 on MRI series from an MRI brain tumor detection dataset for both feature extraction and detection tasks. Compared to other state-of-the-art pre-trained DCNNarchitectures [39], since these models are selected due to their computational efficiency, low FLOPS requirementat inference time, and high top-1 and top-5 accuracyscores on ImageNet [40]. The transfer learning and fine-tuning method, a core part of DL algorithms, utilizes severalhyper-parameters for training and optimization. An opti-mizer, being a critical component in minimizing overall loss.

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CONCLUSION:

The use of MRI for the detection of brain tumors has risenin usage due to the increasing need for efficient and accurateanalysis of vast medical data. Brain tumors, as a life-threatening disease, are challenging owing to tedious manual detection based on medical professionals'expertise. An automatic diagnostic system is a must for the detectionof abnormalities in MRI scans. The proposed method, which uses fine-tuning the pre-trained EfficientNetB4 as its foundation, outperforms many state-of-the-art techniques addressing same classification problems. It attains an exemplary overalltest precision, recall/sensitivity,precision, specificity, F1-score and F2-score of 99.33%, 100%,98.68%, 98.67%, 99.34% and 99.73%, respectively.

In order to make sure the model's robustness is ensured and the modelwill not overfit, K-Fold cross-validation was used and ablind test was undertaken to evaluate the model performanceon an independent dataset. The hyperparameter also was optimized with Bayesian Optimization to detect the best combination. A comprehensive ablation study was conducted to analyze the effect of differentcomponents on the performance of the model, such as testing different batch sizes, dropping layers (like Dropout,Dense, Global Average Pooling, and Flatten layers), modifying optimizers (Adam, SGD, RMSprop, Adagrad), loss functions (binary cross-entropy, hinge, mean squared error), and learning rates (0.01, 0.001, 0.0001), which identified the best configuration and also improved the model's robustness and classification accuracy.In the future, there is scope to investingation there is scope to investigate transformer deep based models for the classification ofMRI brain images.

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