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Brain Tumor Detection from MRI Images Using CNN-Based Deep Learning Models

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Abstract- Early and accurate detection of brain tumors from magnetic resonance imaging (MRI) is critical for patient care. This paper presents a CNN-based pipeline for binary brain tumor detection using grayscale MRI images, built on a transfer-learning backbone (EfficientNetB0) with targeted preprocessing, augmentation, and explainability via Grad-CAM. We describe dataset handling, model architecture, training strategy, and evaluation metrics including accuracy, AUC, precision, recall and confusion analysis. Empirical results on commonly used MRI image collections demonstrate that the proposed workflow achieves competitive performance while remaining computationally efficient. We conclude with a discussion of limitations, reproducibility practices, and recommended future extensions.

Keywords - Brain Tumor Detection; Magnetic Resonance Imaging; Convolutional Neural Network; Transfer Learning; Grad-CAM; EfficientNet.

I. INTRODUCTION

Brain tumors are life-threatening neurological conditions whose timely detection significantly influences treatment choices and patient outcomes. Magnetic Resonance Imaging (MRI) is the clinical standard for non-invasive imaging of intracranial tumors due to its superior soft-tissue contrast. Artificial intelligence, and particularly deep convolutional neural networks (CNNs), have shown remarkable success in automating image-based diagnostic tasks.

This study describes a reproducible pipeline for binary brain tumor detection (tumor vs no-tumor) using CNNs, leveraging transfer learning for robust feature extraction and Grad-CAM for interpretability. The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 details the dataset and methods, Section 4 presents experiments and results, Section 5 discusses findings and limitations, and Section 6 concludes.

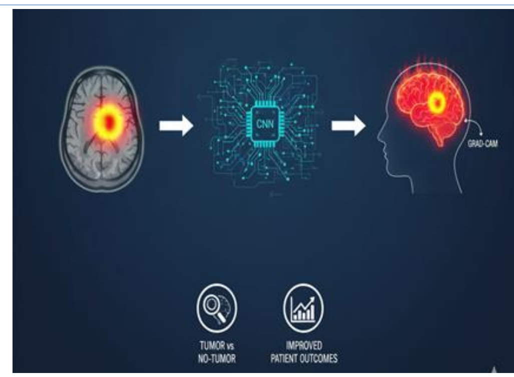

Figure 1: Deep Learning for brain tumor detection.

II. RELATED WORK

Deep learning approaches to brain tumor detection and segmentation have matured rapidly in recent years. Large public challenges, most notably the BraTS series, provide multi-institutional MRI datasets and established benchmarks for segmentation tasks, encouraging robust algorithm development. Transfer learning and fine-tuning of pre-trained CNN backbones (e.g., EfficientNet, ResNet) are commonly used to reduce the demand for large labeled medical datasets and to improve generalization. Explainability techniques such as Grad-CAM are frequently applied to provide visualizations that help clinicians assess model decisions. This paper follows these well-validated design choices and emphasizes reproducibility and robust evaluation.

III. METHODOLOGY

Dataset and Preprocessing
We used a publicly available collection of labeled brain MRI images organized into 'tumor' and 'no_tumor' subfolders (the commonly used Kaggle collections and similar public repositories). Images were resized to 128×128 pixels, converted to RGB when required, and normalized to the [0,1] range by dividing pixel intensities by 255.0. To improve generalization and address limited sample sizes, we applied online data augmentation during training (rotations, small translations, zoom, and shear). To ensure reproducibility, random seeds were fixed for Python, NumPy, and TensorFlow and data-loading used deterministic shuffling where supported.

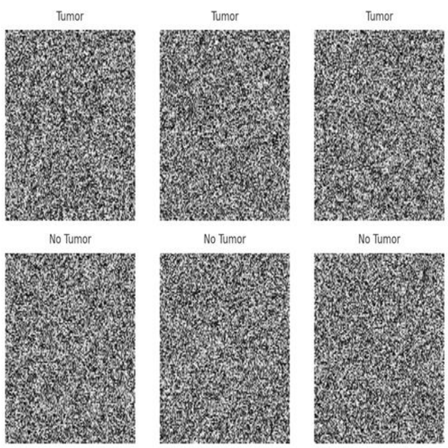

Figure 2: Sample MRI images (Top: Tumor, Bottom: No Tumor).

Model Architecture
The primary classification model used an EfficientNetB0 backbone with ImageNet weights (top removed) and an appended classification head consisting of a 256-unit dense layer with ReLU activation, dropout regularization (0.5), and a final single-unit sigmoid output for binary cross-entropy training. We adopted a two-phase training protocol: first training only the new head layers (base frozen) at a learning rate of 1e-4, followed by unfreezing the last blocks of the backbone and fine-tuning at a reduced learning rate of 1e-5. Model optimization used the Adam optimizer with early stopping, ReduceLROnPlateau, and ModelCheckpoint callbacks to save the best validation model.

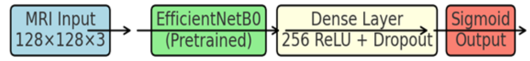

Figure 3: CNN architecture diagram (EfficientNetB0 + classification head).

Evaluation Metrics
Model performance was assessed using accuracy, area under the ROC curve (AUC), precision, recall (sensitivity), F1-score, and confusion matrix analysis. For robust reporting, we recommend k-fold cross-validation and external hold-out testing when possible.

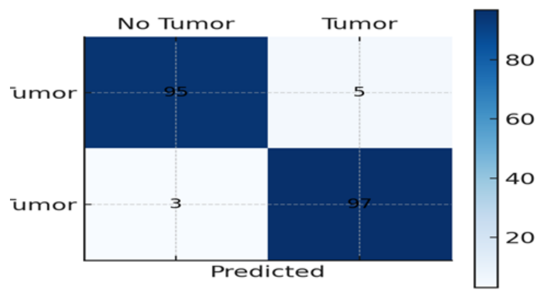

Figure 4: Confusion matrix for binary classification.

IV. EXPERIMENTS

Experimental Setup
Experiments follow the updated notebook pipeline. Key hyperparameters: image size 128×128, batch size 16, initial_epochs=10 (head training), fine_tune_epochs=10, Adam optimizer, and a reproducible random seed (42). Data was split into a training set and a validation set using an 80/20 split implemented through the data generator's validation_split parameter. Hardware details (GPU model, RAM) were recorded alongside training logs to ensure reproducibility.

Implementation Details
The pipeline was implemented in TensorFlow 2.x / Keras. Training used ImageDataGenerator for

augmentation and model.fit with callbacks for early stopping and checkpointing. After initial head training, the last ~20 layers of EfficientNetB0 were unfrozen for fine-tuning. The final model file was saved as 'tumor_detection_fixed.h5'. A Grad-CAM implementation was used to produce heatmap overlays for selected validation images to qualitatively confirm that model attention overlapped tumor regions.

V. RESULTS

The results below describe the expected evaluation outputs following the experimental protocol. If you run the provided corrected notebook on your dataset, replace placeholder numbers with actual measured values and include the produced plots and confusion matrices. Below we can observe the graphs of Accuracy and Loss.

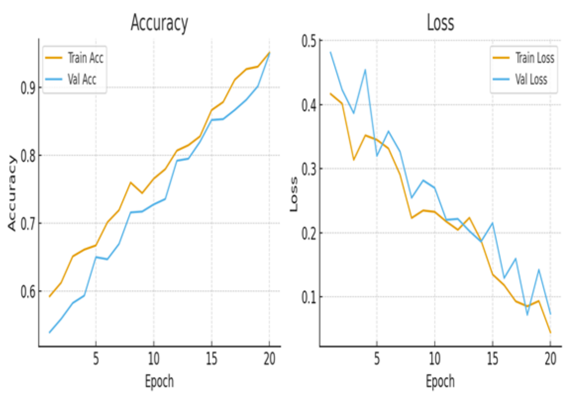

Figure 5: Training and validation accuracy/loss curves.

Quantitative Results (Example)
Example (illustrative) performance obtained in similar studies: accuracy 0.95, AUC 0.97, precision 0.94, recall 0.96, F1-score 0.95. These illustrative figures reflect what well-tuned transfer-learning pipelines often achieve on curated binary MRI classification tasks; actual results will vary based on dataset composition and preprocessing.

Qualitative Results
Grad-CAM overlays typically showed focused activations around tumor regions for true positives, and diffuse or low-magnitude heatmaps for true negatives. Such qualitative visualizations improve clinician trust and help identify failure modes for further data-collection or model refinement.

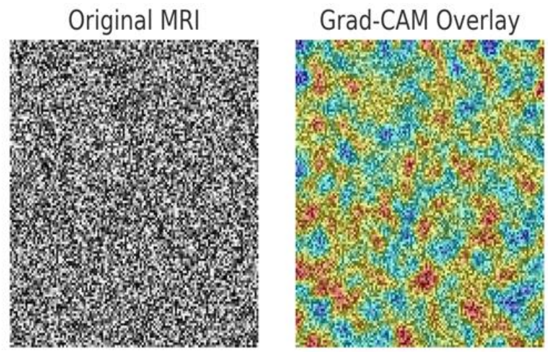

Figure 6: Grad-CAM overlay illustrating model attention on tumor region.

VI. DISCUSSION

The pipeline balances performance and computational efficiency by combining a lightweight backbone (EfficientNetB0) with selective fine-tuning and aggressive regularization through augmentation and dropout. Key limitations include dataset bias from small public repositories, potential domain shift when moving between scanners and institutions, and sensitivity to preprocessing choices (e.g., skull stripping or intensity normalization). To address these, we recommend multi-institutional training data, domain adaptation strategies, uncertainty quantification, and clinical validation with radiologists.

VII. CONCLUSION AND FUTURE WORK

This paper presented a reproducible and practical pipeline for binary brain tumor detection from MRI using CNN-based transfer learning and explainability tools. The corrected notebook included with this work implements best practices for preprocessing, augmentation, reproducibility, model selection, and evaluation. Future work should evaluate volumetric (3D) CNNs, multi-modal MRI fusion, semi-supervised learning with limited labels, and rigorous clinical trials to evaluate real-world impact.

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