Automated Brain Tumor MRI Scans Detection

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Abstract

Brain tumors are serious and potentially life-threatening medical conditions that require early and accurate diagnosis. Manual interpretation of MRI scans can be time-consuming and subject to human error. This project implements a deep learning–based classification system using Convolutional Neural Networks (CNNs), enhanced with transfer learning from the VGG16 model pretrained on ImageNet, to classify MRI brain scans as either tumor or non-tumor. Data augmentation and preprocessing were used to enhance model generalization. The trained model achieved high validation accuracy, demonstrating its potential as a support tool for medical professionals.

Introduction

Brain tumors are abnormal growths of tissue in the brain that can be benign or malignant. The early detection of tumors is crucial for effective treatment and patient survival. Magnetic Resonance Imaging (MRI) is commonly used to diagnose such conditions. However, analyzing large volumes of MRI images manually is challenging and error-prone.

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of image classification, making it a promising approach for automated medical diagnosis. This project explores the use of CNNs combined with transfer learning to classify MRI images into tumor and non-tumor categories with high accuracy.

Aim / Objective

- To design and implement a CNN-based model capable of classifying MRI brain images into tumor and non-tumor classes.
- To compare the performance of basic CNN base model and CNN with pretrained model
- To improve classification performance using transfer learning with a pretrained VGG16 model.
- To apply data augmentation techniques to improve generalization and reduce overfitting.
- To demonstrate its practical utility in clinical decision support systems by evaluating the model's performance on unseen data and visualizing its decision-making process.

Literature Review / Related Work

Several studies have explored the use of deep learning for medical image analysis. Traditional approaches rely on handcrafted features and classical machine learning techniques. However, CNNs have outperformed these methods by automatically learning hierarchical features from raw images.

Transfer learning has further improved performance by allowing models pretrained on large datasets to be **fine-tuned** for smaller medical datasets.

Methodology

Dataset

The dataset used in this notebook is available for download from Kaggle. For this project two classes were used.

- MRI brain scan images categorized into ***Pituitary Tumor*** and **No tumor** classes.
- Split into training and validation datasets using a directory structure for binary classification.
- A subset of 1,000 MRI images was selected, comprising 830 images for training and 170 images for testing. The training set includes 395 images labeled as **No Tumor** and 435 images labeled as **Pituitary Tumor**.

Data Preprocessing

The images are different in size. For CNN for Transfer learning expect all images to have the same size.

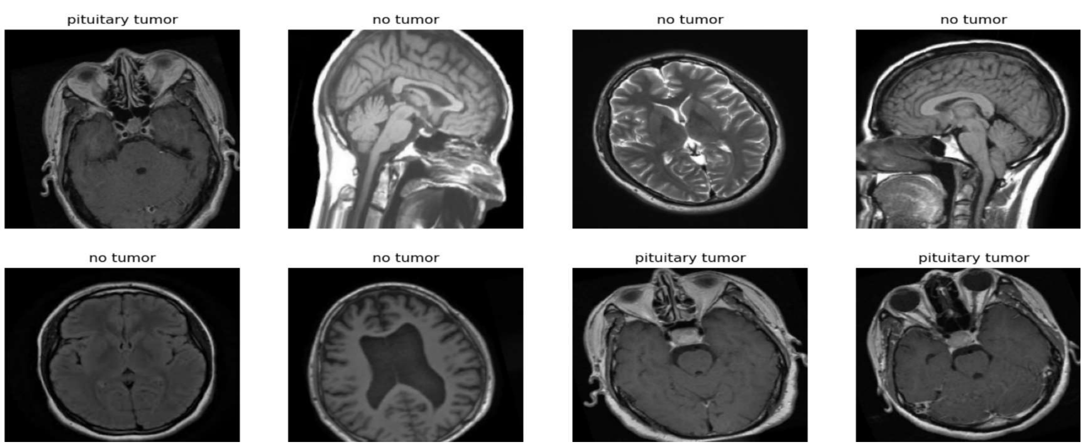

Fig1: Samples of the MRI scans images

- Images were rescaled by 1/255.
- Augmentations included horizontal flip, rotation, shift, shear, and zoom.

Model Architecture

- **Base Model:** VGG16 pretrained on ImageNet,
- Batch Normalization and Dropout layers are used as regularization techniques to prevent overfitting

Results and Evaluation

- The model was trained for 10 epochs with good convergence on training and validation loss.
- Accuracy was evaluated using the `evaluate()` method on validation data.
- The loss vs epoch curve was plotted to visualize learning progression.

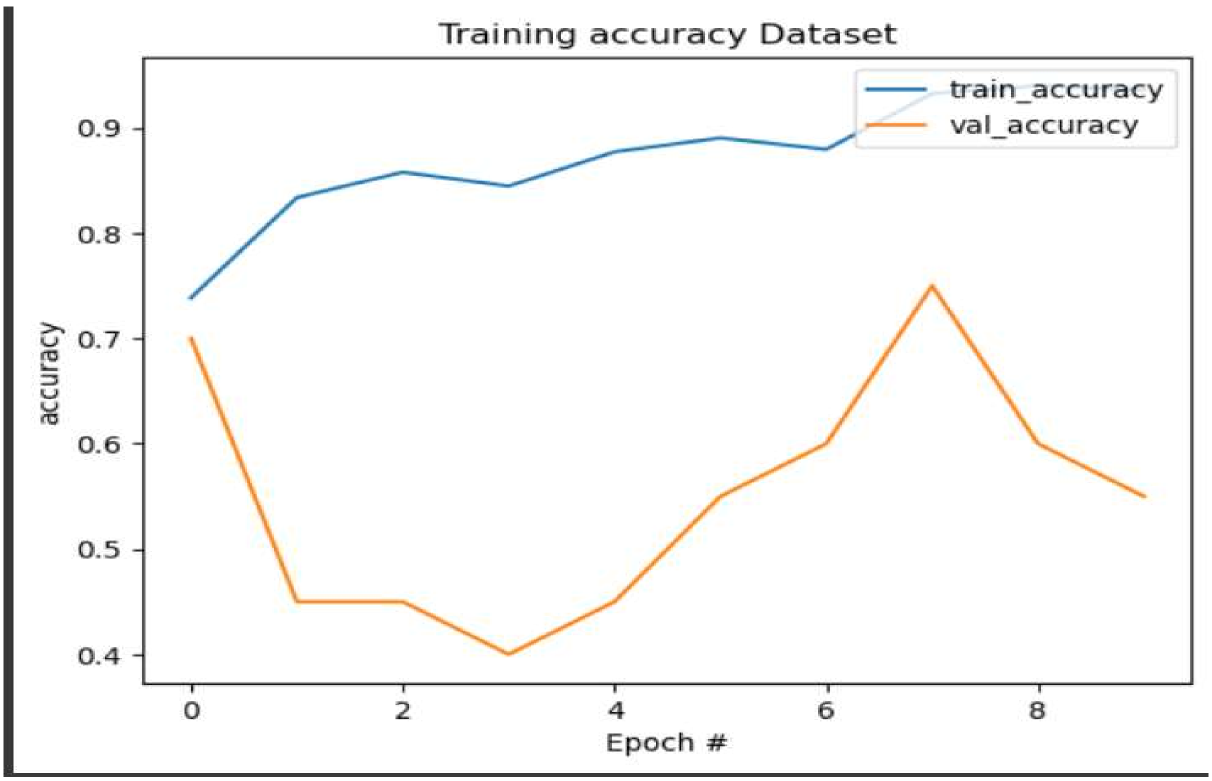

Fig 2: The loss vs epoch curve for the basic CNN model without Transfer Learning

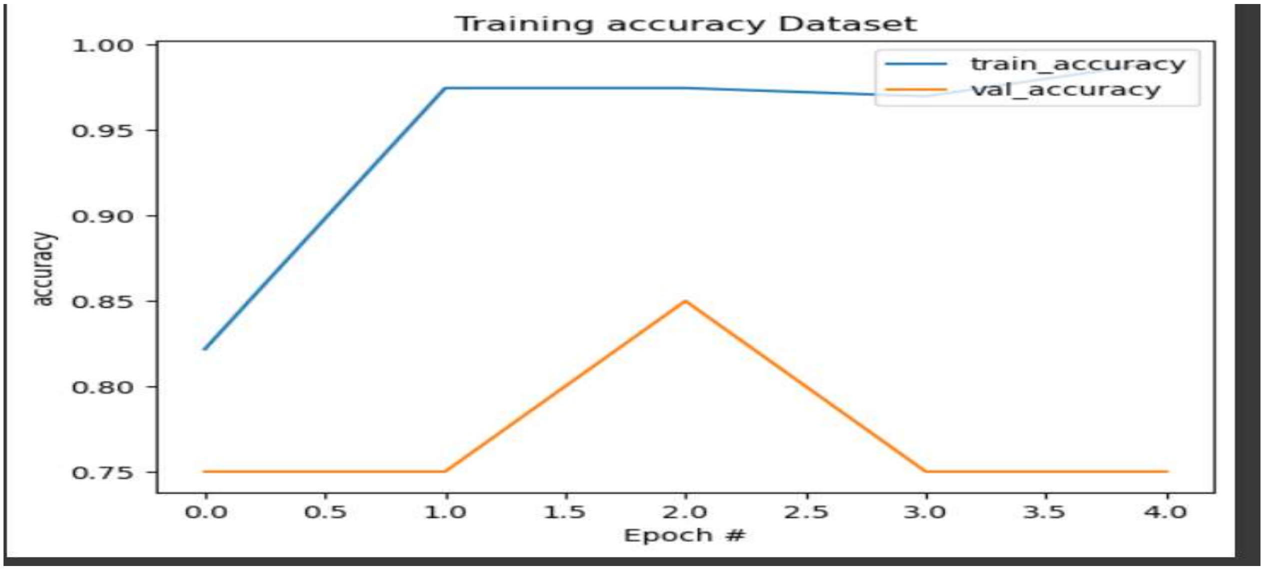

fig 3: The loss vs epoch curve for the Transfer Learning model

Conclusion

This project successfully demonstrated the application of CNNs and transfer learning for brain tumor classification using MRI images. The final model achieved high accuracy and could serve as a clinical decision support tool. However, further validation with larger and more diverse datasets is recommended before real-world deployment.

Limitations

- Model evaluated on a single-center dataset; performance on other scanners or patient populations remains untested.
- Binary classification only—does not differentiate tumor subtypes.

Future Work

- Incorporate more complex architectures (e.g., ResNet, EfficientNet)
- Expand to multi-class tumor subtyping (e.g., glioma vs. meningioma).
- Integrate clinical metadata (age, symptoms) for improved predictive power.

References

1. Simonyan, K., & Zisserman, A. (2014). *Very Deep Convolutional Networks for Large-Scale Image Recognition*. arXiv preprint arXiv:1409.1556.

2. Keras Documentation: https://keras.io
3. ImageNet: https://www.image-net.org/
4. https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri