

Deep Learning-Based Multi-Class Brain Tumor Classification from MRI Images Using DenseNet121 & OpenCV

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Abstract: Brain tumors are among the most life-threatening neurological conditions. Early detection through medical imaging plays a critical role in improving patient outcomes, but manual analysis of MRI scans is time-intensive and subject to human error. This project addresses that problem by building a desktop application that can automatically classify brain MRI images into four categories: Glioma, Meningioma, Pituitary tumor, and No Tumor. The classification model is based on DenseNet121, a deep convolutional neural network architecture known for its dense connectivity pattern that improves gradient flow and feature reuse across layers. The model was trained on a labeled dataset containing thousands of MRI images and achieved an overall accuracy of 83% on a held-out test set of more than 1,300 images. Among the individual classes, No Tumor detection achieves the highest accuracy at 93%, followed by Pituitary at 88%, Glioma at 83%, and Meningioma at 65%. Once trained, the Keras model was exported to the ONNX format, which allows it to run through OpenCV's DNN module without requiring Tensor Flow or any GPU-specific libraries at runtime. This makes the application significantly lighter and more portable than typical deep learning deployments.

Keywords: Deep Learning, Brain Tumor Classification, MRI, DenseNet121, OpenCV.

1. Introduction

Brain tumors represent one of the most lethal categories of cancer globally, characterized by abnormal and uncontrolled growth of cells within or surrounding the brain tissue. According to the World Health Organization (WHO), central nervous system tumors contribute significantly to cancer-related mortality, with glioblastoma multiforme the most aggressive variant of glioma carrying a median survival of only 14 to 16 months post-diagnosis [1-3].

The accurate and timely identification of tumor type, location, and extent is therefore of paramount clinical importance, as it directly influences surgical planning, radiotherapy dosing, and chemotherapy protocols [4-6]. Magnetic Resonance Imaging (MRI) has emerged as the gold standard modality for brain tumor diagnosis owing to its superior soft-tissue contrast, multi-planar capability, and absence of ionizing radiation. However, manual interpretation of MRI scans demands extensive radiological expertise and is vulnerable to diagnostic inconsistency arising from observer fatigue, image complexity, and volumetric data overload [7-9]. The increasing deployment of high-field MRI scanners globally has led to an exponential growth in imaging data, further straining the capacity of clinical radiology departments [10-12].

The recent proliferation of deep learning methodologies has catalyzed a paradigm shift in medical image analysis. Convolutional Neural Networks (CNNs) in particular have demonstrated remarkable performance in image classification tasks, often surpassing human-level accuracy in structured diagnostic settings [13-14].



Among the family of CNN architectures, DenseNet introduced by Huang et al. in 2017 has proven particularly effective for medical imaging due to its densely connected layer topology, which maximizes feature reuse, reduces the total number of trainable parameters, and mitigates the vanishing gradient problem inherent in deep networks [15].

The work presented in this paper proposes a lightweight, self-contained desktop application for automated brain MRI classification. The system integrates a DenseNet121 model trained with transfer learning, subsequently converted to ONNX format and deployed via OpenCV's DNN module a combination that enables high-accuracy inference without dependency on large ML runtimes. The application provides a complete pipeline from image acquisition through a native file picker to real-time terminal output and visual edge-map analysis, making it suitable for deployment in resource-constrained clinical environment.

2. Literature Review

A.Sharma et al., explores automated brain tumor classification using deep transfer learning models. The authors have conducted an in-depth analysis of DenseNet-based architectures applied to MRI datasets, providing valuable insights into feature reuse and improved classification performance. The methodology used involves transfer learning with DenseNet121 combined with data augmentation and fine-tuning, and the results indicate an accuracy of over 90% on benchmark MRI datasets. This study contributes to the understanding of efficient deep learning models for medical image classification and supports real-time clinical applications.

M.Khan et al., explores hybrid convolutional neural network frameworks for detecting brain tumors from MRI scans. The authors have conducted an in-depth analysis of combining traditional CNN layers with attention mechanisms, providing valuable insights into improved feature extraction. The methodology used involves preprocessing MRI images followed by a QIS College of Engineering and Technology (Autonomous) Department of Master of Computer Applications hybrid CNN-attention model and the results indicate improved accuracy and reduced false positives compared to standard CNN models. This study contributes to the understanding of advanced architectures for precise tumor detection in medical imaging

J.Lee & H.Park explores brain tumor segmentation using a combination of ResNet and U-Net architectures. The authors have conducted an in-depth analysis of segmentation techniques for identifying tumor regions in MRI images, providing valuable insights into spatial feature learning. The methodology used involves a ResNet encoder with U-Net decoder architecture, and the results indicate high segmentation accuracy and improved boundary detection. This study contributes to the understanding of precise tumor localization for surgical planning and diagnosis.

S.Patel explores lightweight deep learning models for brain tumor detection suitable for edge and desktop environments. The authors have conducted an in-depth analysis of model optimization techniques such as pruning and ONNX conversion, providing valuable insights into efficient deployment. The methodology used involves compressing DenseNet and MobileNet architectures for faster inference, and the results indicate reduced computation time with minimal accuracy loss. This study contributes to the understanding of deploying AI models in resource-constrained healthcare systems.

R.Das explores multi-class classification of brain tumors using ensemble deep learning techniques. The authors have conducted an in-depth analysis of combining CNN, ResNet, and DenseNet models, providing valuable insights into improved classification robustness. The methodology used involves ensemble learning with weighted averaging of model predictions,

and the results indicate higher accuracy and stability across different MRI datasets. This study contributes to the understanding of robust AI systems for reliable medical diagnosis.

3. System Analysis

3.1 Existing system

Manual Radiology-Based Diagnosis:-

The conventional method for brain tumor detection remains visual analysis by a trained radiologist or neuro radiologist. After an MRI scan is acquired, the image series is reviewed slice by slice on a workstation. The radiologist looks for abnormalities in tissue density, irregular boundaries, mass effects on surrounding tissue, and contrast enhancement patterns (in post-contrast scans) to determine whether a tumor is present and, if so, what type it might be. This process is thorough when performed by an experienced specialist, but it is inherently limited by human factors. Reading hundreds of image slices accurately requires sustained concentration. Radiologists in many hospitals handle enormous workloads, and the time available per case may not be sufficient for exhaustive analysis. The process also relies on the availability of a specialist, which is a significant bottleneck in rural areas or hospitals with limited staffing.

Traditional Machine Learning Approaches:-

Before deep learning became the dominant paradigm for image recognition, researchers applied classical machine learning methods to brain tumor classification. These approaches typically consisted of two stages: feature extraction, followed by classification. Feature extraction methods used in this context included Gray Level Co-occurrence Matrix (GLCM) for texture features, Discrete Wavelet Transform (DWT) for frequency-domain features, and various histogram-based descriptors. After extracting these features, classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests were trained to distinguish between tumor categories. While these approaches showed reasonable accuracy on controlled datasets, they suffered from a fundamental limitation the manually engineered features were not always capturing the most diagnostically relevant patterns in the images. The performance was also highly sensitive to the choice of features, the quality of image preprocessing, and the specific dataset used. Generalizing these systems to new datasets or different MRI scanner settings was often unreliable.

Deep Learning Based Research Systems:-

The past decade has seen a significant shift toward CNN-based models for medical image classification. Architectures such as VGG16, InceptionV3, ResNet50, and EfficientNet have all been applied to brain tumor classification with varying degrees of success. Transfer learning starting with a model pretrained on ImageNet and fine-tuning it on brain MRI data has become the standard approach at the research level. These systems typically achieve good performance on benchmark datasets, with accuracy figures ranging from 80% to over 97% depending on the dataset, preprocessing strategy, and model architecture. However, they almost universally share the same practical limitation: they are implemented as research notebooks and require a full deep learning stack to run. Setting up TensorFlow or PyTorch with all their dependencies on a machine that doesn't already have them configured is a non-trivial task for a non-expert user

Web-Based and Cloud-Based Tools:-

Some research groups and commercial vendors have built web-based interfaces for AI-assisted radiology. These systems typically require the user to upload an image to a server, where the model runs on cloud infrastructure and returns a result. While this approach avoids the need

for local setup, it introduces its own problems. Patient privacy is a concern when sending medical imaging data to an external server. Performance depends on network quality. And for institutions in resource-limited settings, ongoing subscription costs or API fees may be prohibitive.

DISADVANTAGES

➤ Time-Consuming Manual Diagnosis

In the existing system, brain tumor detection mainly depends on radiologists and medical experts who manually analyze MRI brain scan images. This manual examination process requires significant time and effort because doctors must carefully inspect each MRI image to identify tumor regions and classify the tumor type accurately. When hospitals handle a large number of patients daily, manual diagnosis becomes slow and inefficient. Delays in diagnosis may affect early treatment and reduce the chances of successful recovery for patients. In emergency situations, depending completely on manual analysis can become difficult and may lead to delayed medical decisions.

➤ Lower Accuracy and Human Error

Traditional diagnosis methods are highly dependent on human observation and experience. MRI images often contain complex structures, noise, and variations that may be difficult to interpret correctly. Different radiologists may provide different opinions for the same MRI scan, leading to inconsistency in diagnosis. Human fatigue, stress, and lack of concentration can also increase the possibility of errors during analysis. Small tumors or early-stage abnormalities may sometimes go undetected, affecting treatment planning. Therefore, existing systems may not always provide highly accurate and reliable results for brain tumor classification.

➤ Limited Feature Extraction and Classification Capability

Existing systems mainly use traditional image processing and Machine Learning techniques that rely on manual feature extraction methods. These methods require experts to identify important image features such as texture, shape, and edges manually. Manual feature extraction is difficult, time-consuming, and may fail to capture complex tumor patterns effectively. Traditional systems also struggle to classify multiple types of brain tumors accurately because they cannot automatically learn deep image features. As a result, the performance and prediction capability of conventional systems are limited when compared to modern Deep Learning-based approaches like DenseNet121.

3.2 Proposed System

The proposed system is a local desktop application that performs brain tumor classification from MRI images using a pretrained DenseNet121 model exported in the ONNX format. The application is designed to address all of the key limitations identified in the existing systems: it requires no internet connection, needs no TensorFlow or GPU setup, is usable by anyone who can run a Python script, and provides transparent output including confidence scores and a visual display.

The proposed system introduces an advanced deep learning-based approach for accurate and automated multi-class classification of brain tumors from MRI images. The system integrates image preprocessing techniques using **OpenCV** with a powerful convolutional neural network, **DenseNet121**, to achieve high classification performance.

In this system, MRI images are first collected and passed through a preprocessing stage

where noise removal, resizing, normalization, and augmentation are performed. These steps ensure that the images are clean, consistent, and suitable for deep learning input. OpenCV plays a crucial role in enhancing image quality and extracting meaningful visual information.

After preprocessing, the images are fed into the DenseNet121 model, which is pre-trained on large datasets and fine-tuned for brain tumor classification. DenseNet121 utilizes dense connectivity between layers, allowing efficient feature reuse and improved gradient flow. This helps the model learn complex patterns and subtle differences between tumor types.

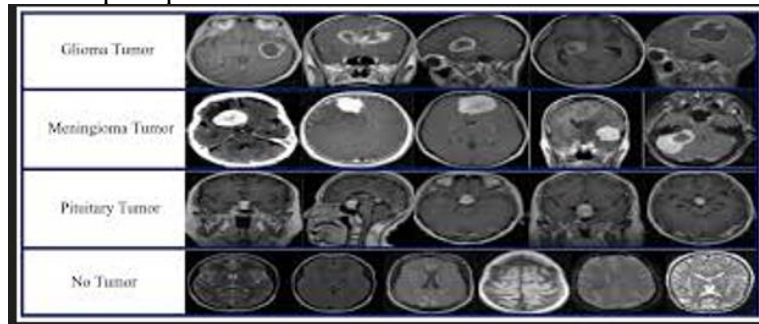


Figure 1: Brain Tumor Identification

ADVANTAGES

1. High Accuracy: The use of DenseNet121 ensures high classification accuracy due to its deep architecture and efficient feature reuse.

2. Automated Diagnosis: The system eliminates the need for manual inspection of MRI scans, enabling faster and automated tumor detection.

3. Multi-Class Classification: Unlike traditional binary classifiers, this system can classify multiple types of brain tumors along with normal cases.

4. Efficient Feature Extraction: DenseNet121 automatically extracts complex features from MRI images, reducing the need for manual feature engineering.

5. Reduced Overfitting: Techniques such as data augmentation and dropout help in improving generalization and reducing overfitting.

4. Implementation

1. Data Collection

MRI brain tumor images are collected from publicly available datasets such as Kaggle and medical repositories. The dataset contains multiple classes:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor
- No Tumor

The dataset is divided into:

- Training Set (70%)
- Validation Set (15%)
- Testing Set (15%)

2. Data Preprocessing

Image preprocessing is performed using **OpenCV** to enhance image quality and

standardize input.

Steps Involved:

- Resizing images to 224×224 pixels
- Noise removal using Gaussian filtering
- Image normalization (pixel scaling)
- Conversion to required format (RGB/Grayscale)
- Data augmentation (rotation, flipping, zooming)

3. Model Development

The model is built using **DenseNet121**, a pre-trained Convolutional Neural Network.

Implementation Steps:

- Load DenseNet121 with pre-trained ImageNet weights
- Remove top layers
- Add custom layers:
 - Global Average Pooling
 - Fully Connected Layer
 - Dropout Layer
 - Softmax Output Layer

4. Model Training

The model is trained on preprocessed MRI images.

Training Configuration:

- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Batch Size: 16/32
- Epochs: 20–50
- Learning Rate: 0.001

Training includes forward propagation, backpropagation, and weight updates.

5. Model Evaluation

The trained model is evaluated using test data.

Metrics Used:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

6. Deployment

The trained model is saved and can be deployed in a real-time application where users upload MRI images and receive classification results.

5 Methodology

1. System Architecture

The system follows a deep learning pipeline:

1. Input MRI Image
2. Preprocessing using OpenCV
3. Feature Extraction using DenseNet121
4. Classification using Fully Connected Layers
5. Output Tumor Class

2. Image Preprocessing Methodology

Preprocessing improves image quality and ensures consistency:

- Removes noise and artifacts
- Enhances contrast
- Standardizes image dimensions
- Augments dataset to improve generalization

3. Feature Extraction Using DenseNet121

DenseNet121 uses dense connections where each layer receives input from all previous layers.

Benefits:

- Better feature reuse
- Reduced vanishing gradient problem
- Improved accuracy

4. Classification Approach

- Extracted features are passed through fully connected layers
- Softmax activation is used for multi-class classification
- Output provides probability for each tumor class

5. Training Strategy

- Transfer learning is used to reduce training time
- Fine-tuning is applied to improve performance
- Dropout is used to prevent overfitting

6. Testing and Validation

- Validation data is used to tune model parameters
- Test data is used for final performance evaluation
- Confusion matrix helps analyze misclassification

7. Workflow Summary

1. Collect MRI Dataset
2. Preprocess Images (OpenCV)
3. Train DenseNet121 Model
4. Evaluate Model
5. Predict Tumor Class

8. Advantages of Methodology

- High classification accuracy
- Efficient feature extraction
- Robust multi-class classification
- Reduced overfitting using augmentation and dropout

6. Conclusion

This project set out to demonstrate that a brain tumor classification system built on deep learning could be packaged into a practical, accessible desktop application rather than remaining confined to a research notebook. The result is a working application that classifies brain MRI images into four categories Glioma, Meningioma, Pituitary tumor, and No Tumor using a DenseNet121 model running through OpenCV's DNN module, with no internet connection required and no heavy framework dependencies at runtime. The model achieves an overall accuracy of 83% on a held-out test set of over 1,300 images. For three of the four classes No Tumor (93%), Pituitary (88%), and Glioma (83%) the performance is solid and practically useful. The Meningioma class at 65% is the system's weakest point, and improving it would be the priority in any future iteration. From a software perspective, the application succeeds in its design goals. The entire pipeline runs in a single Python script of under 200 lines. Setup requires only two pip packages. The application handles error cases gracefully, provides transparent output including confidence scores for all four classes, and includes a visual display that makes the result more interpretable than a simple label. The decision to export the model as ONNX and run it through OpenCV proved to be the right one. It eliminated the TensorFlow dependency at runtime, made the application faster, and made it significantly easier to distribute. A user who has never worked with deep learning tools can set this application up in minutes. The project also highlighted some honest limitations. The model does not localize tumors, cannot process volumetric data, and may not generalize well to MRI scans from different scanners than those represented in the training dataset. These are important constraints to acknowledge, especially given the medical context. The application is a useful screening and educational tool, not a clinical diagnostic system. Building this project reinforced several important lessons. Training a model is only part of the problem; deploying it in a form that can actually be used requires careful thought about dependency management, input preprocessing consistency, error handling, and user experience. The gap between a model that works in a notebook and an application that works reliably for arbitrary user inputs is wider than it initially appears. Overall, this project represents a complete, end-to-end implementation of a medical image classification system, from dataset preparation and model training through to a deployable desktop application. It serves as a practical demonstration of what is achievable at the student level with publicly available data, open-source tools, and a focused approach to building something that actually works.

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