Detection of Brain Tumor from Mri Images Using Image Processing and Machine Learning

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***Abstract*—Brain tumor detection through MRI analysis plays a pivotal role in neuro-oncology, demanding both precision and efficiency. Manual diagnosis, although widely practiced, is often limited by subjectivity and variability. To address these challenges, this project presents an automated brain tumor classification system leveraging deep learning and transfer learning. The proposed pipeline incorporates advanced image preprocessing techniques such as cropping, denoising, and normalization, followed by data augmentation to address class imbalance. ResNet152, a state-of-the-art convolutional neural network, is fine-tuned using MRI images to classify tumors into four categories: glioma, meningioma, pituitary, and no tumor. The model achieves high classification accuracy, validated through multiple metrics, and demonstrates significant potential as a decision-support tool in clinical settings.**

Index Terms*—*Brain Tumor, Image Processing, MRI Images, ResNet 152, Deep Learning

I. INTRODUCTION

Brain tumors are among the most life-threatening medical conditions, with early diagnosis playing a crucial role in effective treatment and improved patient prognosis. Magnetic Resonance Imaging (MRI) is commonly used for non-invasive brain imaging, offering detailed structural information. However, manual interpretation of these scans is time-consuming and prone to human error, especially given the variability in tumor morphology and intensity.

Recent advances in artificial intelligence, particularly in deep learning, have shown tremendous promise in automating medical image analysis. Convolutional Neural Networks (CNNs) have proven effective in learning complex features from imaging data, making them suitable for tasks like tumor classification. However, training deep models from scratch requires large labeled datasets, which are often scarce in the medical domain.

To overcome these limitations, we adopt transfer learning using ResNet152, a deep CNN pre-trained on the ImageNet dataset. By fine-tuning this model on a curated MRI dataset, we aim to build a robust classification system for brain tumors. This work also emphasizes image preprocessing, including cropping based on contour detection, denoising, normalization, and class balancing through data augmentation, to enhance model performance.

II. RELATED WORK

Numerous studies have explored the application of machine learning and deep learning techniques for brain tumor detection from MRI images. Asiri et al. (2024) proposed a dual-module approach that combines adaptive Wiener filtering with neural networks and Independent Component Analysis (ICA) to enhance the speed and accuracy of brain tumor detection. While their method showed improved performance, it lacked robustness across diverse classifiers, indicating the need for a more standardized detection framework.

Sumit and Ambuj (2024) focused on the early detection of brain tumors using various machine learning techniques, particularly convolutional neural networks (CNNs) combined with preprocessing strategies. Although their approach demonstrated promising results, the inherent variability and complexity of MRI scans posed significant challenges, particularly in achieving reliable and precise segmentation.

In another study, Anantharajan (2024) introduced an advanced AI-driven method employing EfficientNet-B2 along with homomorphic filtering and image equalization to boost detection performance. While effective, the model required high computational resources, which could hinder its practical use in standard clinical settings with limited infrastructure.

Rahman (2024) proposed a hybrid deep learning model that integrates ensemble techniques to improve classification accuracy. Although the ensemble-based approach yielded strong results, it remained dependent on radiological expertise for effective implementation, thereby limiting its automation potential.

These studies underscore the ongoing efforts to optimize brain tumor detection through AI, yet they also highlight critical gaps such as limited robustness, high computational cost, and dependency on domain experts. Our proposed method seeks to address these challenges by leveraging transfer learning with ResNet152, combined with advanced preprocessing and augmentation, to build a scalable, efficient, and accurate brain tumor classification system.

III. PROBLEM STATEMENT

Early and accurate detection of brain tumors is vital for effective clinical diagnosis and treatment planning. Traditionally, radiologists analyze MRI scans manually to identify tumors, a process that is often time-consuming, error-prone, and subject to inter-observer variability due to the complexity and subtlety of tumor features. Furthermore, in resource-constrained environments, there may be a lack of access to specialized medical personnel or timely diagnostic services.

To address these issues, there is a growing need for an automated, reliable, and accessible system that supports medical professionals in diagnosing brain tumors. In this project, we aim to fill this gap by developing an intelligent support system that allows users—particularly healthcare providers—to upload MRI images through a user-friendly interface and automatically detect and classify brain tumors using deep learning techniques. This system not only enhances diagnostic speed and consistency but also serves as a valuable second opinion for clinicians, improving decision-making and patient outcomes.

IV. OBJECTIVES

1. To design an automated brain tumor classification system using deep learning and transfer learning.
2. To apply advanced image preprocessing techniques such as cropping, denoising, and normalization for noise reduction and focus enhancement.
3. To implement data augmentation strategies to address class imbalance and improve generalization.
4. To evaluate the performance of the proposed system using metrics such as accuracy, precision, recall, and F1-score.
5. To compare the model's effectiveness with existing approaches from the literature.

V. METHODOLOGY

Dataset

The dataset used in this study comprises pre-labeled MRI images divided into four categories: glioma, meningioma, pituitary tumor, and no tumor. The data is structured into separate training and testing folders. Images vary in resolution and quality, necessitating thorough preprocessing.

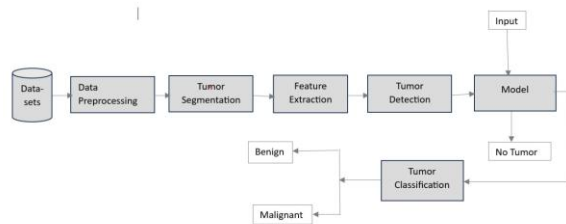

Figure no 1: System Architecture

Preprocessing Pipeline

To ensure consistent input to the model and improve detection accuracy, several image preprocessing steps were applied:

Cropping: Using contour detection and extreme point localization, each image is cropped to isolate the brain region, eliminating irrelevant background artifacts. Resizing: All cropped images are resized to a standard shape of 224×224 pixels to match the input dimensions of ResNet152. Denoising: Bilateral filtering is applied to preserve edges while reducing noise.

Colormap Enhancement: The 'bone' colormap is used to highlight structural details relevant to tumor detection.

Normalization: Pixel intensities are normalized to the range [0, 1].

Data Augmentation

Due to class imbalance in the training set, a class-specific augmentation strategy is employed using techniques like:

Random rotations Horizontal flips Width and height shifts This step increased the number of samples in underrepresented classes, enhancing the model's generalization capability.

Model Architecture

We leverage ResNet152 via transfer learning, using pre-trained weights from ImageNet. The architecture includes:

Base model**:** ResNet152 with include_top=False.

Top layers:

- Global Average Pooling layer
- Dropout layer (rate = 0.4) to reduce overfitting
- Dense layer with softmax activation for 4-class classification

All layers are made trainable to allow full fine-tuning on medical data.

Training Configuration

- Loss Function: Categorical Crossentropy
- Optimizer: Adam with a learning rate of 0.0001
- Callbacks: ReduceLROnPlateau and ModelCheckpoint
- Epochs: 50
- Batch Size: 32
- Validation Split: 20% of the dataset

VI. EXPERIMENTS AND RESULTS

To evaluate the effectiveness of the proposed brain tumor classification system, several key performance metrics were calculated, including precision, recall, F1-score, and overall accuracy. The model was tested on a dataset of 1,405 MRI images spanning four tumor classes: glioma (0), meningioma (1), no tumor (2), and pituitary (3).

The classification report demonstrates outstanding performance across all classes. The model achieved an overall accuracy of 99%, indicating excellent generalization to unseen data. The macro average and weighted average values for precision, recall, and F1-score were all 0.99, highlighting the balanced performance across all tumor types despite slight class imbalance.

- Class 0 (Glioma): Precision and F1-score of 1.00, recall of 0.99
- Class 1 (Meningioma): Precision of 0.98, recall of 0.97, F1-score of 0.98
- Class 2 (No Tumor): Perfect precision and F1-score of 1.00, recall of 0.99
- Class 3 (Pituitary Tumor): Precision of 0.97, recall of 0.99, F1-score of 0.98

The confusion matrix further confirms the model's strong classification ability, showing minimal misclassifications. For example:

- Only 2 glioma cases were misclassified,
- 8 meningioma cases were incorrectly labeled as pituitary tumors,
- No tumor and pituitary classes had only 1–2 misclassifications each.

This consistent performance across all categories demonstrates the model's robustness and reliability, making it a suitable candidate for integration into clinical decision support systems.

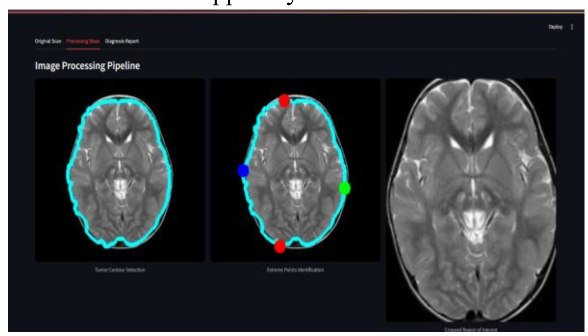

Figure No 2: Tumor contour detection & Extreme point identification

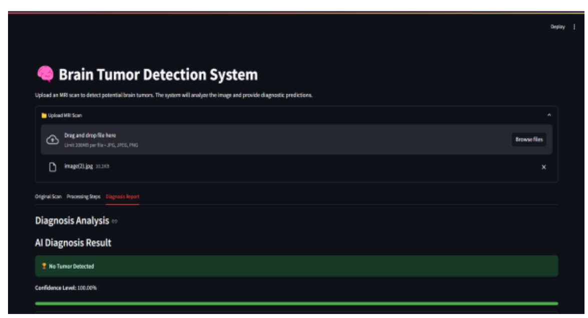

Figure No 3: Tumor detection status

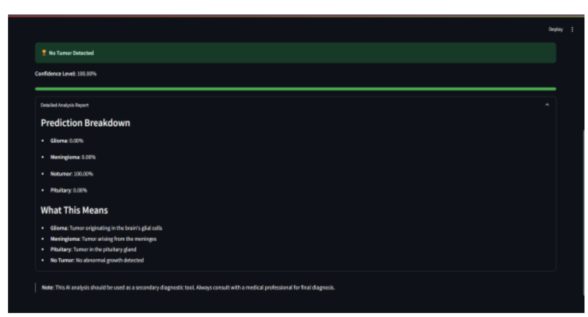

Figure No 4: Tumor classification result

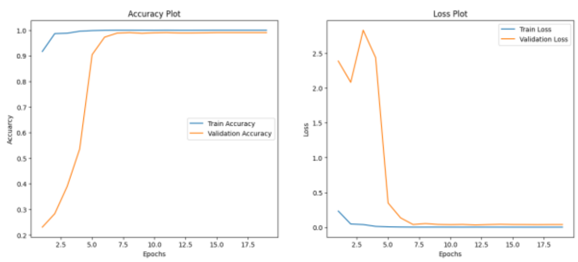

Figure No. 5: Model Accuracy Graph

VII. CONCLUSION

This study demonstrated the effectiveness of transfer learning using the ResNet152 architecture combined with advanced image preprocessing techniques—such as cropping, denoising, normalization, and data augmentation—in accurately detecting brain tumors from medical images. The incorporation of these preprocessing steps significantly enhanced the quality of the input data, allowing the deep learning model to better capture relevant features and improve classification performance. Transfer learning leveraged the powerful feature extraction capabilities of ResNet152, reducing the need for extensive training data while maintaining high accuracy. Overall, the proposed approach shows great promise for assisting radiologists in early and reliable brain tumor diagnosis, potentially contributing to improved patient outcomes. Future work may focus on expanding the dataset diversity, refining preprocessing pipelines, and integrating the model into clinical decision-support systems for real-time application.

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