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BRAIN TUMOR DETECTION USING MACHINE LEARNING

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Abstract

The main purpose of this work is to detect the presence of a brain tumor from MRI images using image processing and deep learning techniques. A brain tumor is caused by the abnormal and uncontrolled growth of cells inside the brain. Early detection plays a major role in improving the success rate of treatment and reducing the risk of death. In this study, MRI images are used because they provide better visibility of brain tissues compared to other medical imaging methods. The preprocessing step includes image enhancement, skull stripping, segmentation, and morphological operations to clearly separate the tumor region. After segmentation, a Convolutional Neural Network (CNN) model is trained to identify whether the MRI image contains a tumor or not. The segmented region is then used to estimate the tumor size and affected area density. The proposed approach helps in automatic detection and analysis of brain tumors, which can support doctors in making faster and more accurate diagnoses.

Keywords: CNN, Brain Tumor, Image Processing, Image Segmentation, ROI.

1 Introduction

Please Brain tumor detection is an important research area in medical imaging because early identification of the tumor can save a patient's life. A brain tumor occurs when cells in the brain start to grow abnormally and form a mass. These tumors can be benign (non-cancerous) or malignant (cancerous). Magnetic Resonance Imaging (MRI) is one of the most widely used scanning techniques for detecting and studying brain tumor since it provides high-resolution images of soft tissues. In recent years, image processing and deep learning have been widely used in the medical field to analyze MRI images for better diagnosis.

Brain tumor may cause several symptoms depending on their location in the brain. Common symptoms include frequent headaches, memory loss, nausea, dizziness, and vision problems. The major reasons for brain tumor development may include genetic factors, radiation exposure, head injuries, or infections. Based on the level of severity, brain tumor categorized into different grades by the World Health Organization (WHO).

Traditional diagnosis methods involve manual inspection of MRI images by radiologists, which can be time-consuming and sometimes prone to human error. To overcome these limitations, computer-based methods are being developed to automatically detect and classify brain tumor from medical images. Deep learning, especially Convolutional Neural Networks (CNN), has shown high accuracy in identifying patterns and features in MRI scans. CNNs

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can automatically learn the important features from images without the need for manual feature extraction.

The main goal of this paper is to build an automated brain tumor detection model using CNN and image processing techniques. The process includes image preprocessing, segmentation, and tumor detection. The proposed system is evaluated and compared with existing methods to check its performance and accuracy. The results show that the CNN model can efficiently detect and classify brain tumor, which can help medical experts in better treatment planning and patient care.

2 Related work

Yadav et al. (2024). In this study, a modified ResNet-50 architecture was used for brain tumor detection. The convolutional layers were optimized to improve feature extraction and reduce overfitting. The authors tested their model on MRI images and reported higher accuracy compared to traditional CNNs. The work highlighted that deep residual layers help the network learn complex tumor patterns efficiently.

Vinu et al. (2024). This paper focused on accurate brain tumor segmentation using an enhanced CNN along with traditional machine learning classifiers. The model first segmented the tumor area from MRI images and then classified it into specific tumor types. The proposed hybrid CNN method showed improved segmentation accuracy and reduced false detections, which can assist doctors in better diagnosis.

Abdusalomov et al. (2023) presents an advanced deep learning framework for accurate brain tumor detection using magnetic resonance imaging (MRI). The authors leverage multiple convolutional architectures to enhance classification precision and automate diagnostic processes. The proposed model demonstrates high accuracy and robustness, contributing significantly to computer-aided medical diagnosis.

Islam et al. (2023). This study carried out a detailed investigation on the use of CNNs, clustering techniques, and SoftMax classifiers for brain tumor detection. The paper compared several architectures and found that CNN models outperform classical clustering-based approaches. Their experiments demonstrated that deep learning techniques can provide reliable results even with limited MRI data.

Shawon et al. (2023). The authors introduced an explainable cost-sensitive deep neural network for handling imbalanced MRI datasets. They focused on improving tumor detection for minority classes and provided visual explanations for model predictions. The proposed approach achieved better sensitivity and interpretability compared to baseline CNN models.

Reddy et al. (2023). Reddy and co-authors used deep CNN models combined with selected machine learning techniques to detect brain tumors from MRI images. The paper compared CNN with SVM and Random Forest models. Results showed that CNN performed the best in terms of both accuracy and robustness. The study concluded that deep learning can effectively replace manual diagnosis in many medical imaging tasks.

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Namachivayam and Puviarasan (2023). This work proposed a computerized classification system for brain tumors using MRI images. The authors used image enhancement and texture-based feature extraction methods before applying CNN classification. The system achieved good accuracy and was capable of automatically identifying tumor regions without human assistance.

Khochare et al. (2023). The authors performed a CNN-based multiclass analysis on MRI brain images to classify glioma, meningioma, and pituitary tumors. Their approach used preprocessing and augmentation to increase data variability. The model achieved strong classification accuracy and showed that CNNs can effectively learn texture differences between tumor types.

Shaimaa et al. (2023). A Robust MRI-Based Brain Tumor Classification via a Hybrid Deep Learning Technique (2023). This paper introduced a hybrid deep learning framework combining CNN and LSTM layers to improve tumor classification accuracy. The CNN part extracted spatial features, while the LSTM captured long-range dependencies in MRI sequences. The hybrid model achieved higher precision and stability compared to single CNN models.

3 Proposed Method

The main goal is to classify brain MRI images into four categories — *glioma, meningioma, pituitary, and no-tumor*, by training a Convolutional Neural Network (CNN) on the Region of Interest (ROI) of each image. The proposed system focuses on removing the unwanted parts of the MRI and using only the important brain region for better accuracy. The overall process is divided into several stages such as image acquisition, preprocessing, segmentation, and feature extraction.

Below Fig 1. Represents the proposed architectures which in implemented in the paper.

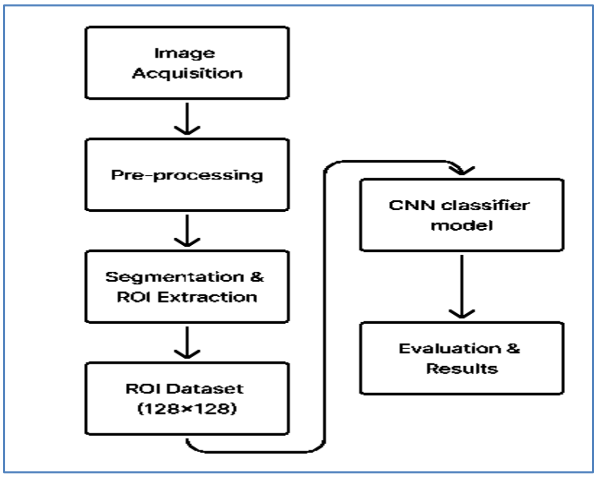

Fig 1. Proposed architecture.

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3.1 Image Acquisition

We used the public ‘Brain Tumor MRI Dataset’ (Masoud Nickparvar) from Kaggle. The dataset contains total 7023 MRI images grouped into four classes: *glioma, meningioma, pituitary tumor, and no tumor.* The original folder structure provided separate Training and Testing sets.

3.2 Pre processing

Preprocessing is done to improve image quality and prepare data for the segmentation and classification process**.** Contrast enhancement was applied using CLAHE (Contrast Limited Adaptive Histogram Equalization) with a tile gridSize of (8,8) and clipLimitt of 2.0. Pixel intensities were rescaled to [0,1] prior to network input. Below are the series of steps that are followed in preprocessing stage.

1. Image Loading: Each MRI image is loaded in grayscale mode using OpenCV.
2. Contrast Enhancement: The CLAHE (Contrast Limited Adaptive Histogram Equalization) method is applied to enhance contrast and make tumor regions more visible.
3. Intensity Normalization: The image pixels are normalized to bring values within a standard range, which helps the CNN learn effectively.

3.3 Image Segmentation and ROI Extraction

The ROI based Segmentation is performed to isolate the brain region from the surrounding skull and background. This helps the classifier model to focus on the anatomically relevant area, a light-weight classical segmentation pipeline was applied to every image to separate the brain from skull and background.

1. Otsu thresholding on CLAHE-enhanced images that separates the brain from the background.
2. Morphological operations done to remove small noisy areas from the image.
3. Only the largest connected component (the brain region) is kept, assuming it represents the main area of interest.
4. Bounding-box extraction of the brain mask and cropping with a 5-pixel padding. If a brain mask could not be extracted, the full image was resized to the target size and used as fallback.

The ROI images (128×128) were saved to a new dataset directory maintaining the original class labels and split semantics (Train/Test). This transformed dataset is the input to the deep learning classifier.

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4 Experiment and Result

The ROI images of size (128 x 128) is served as input to CNN classifier model that consists of three convolutional blocks with increasing filter sizes (32, 64, 128), each followed by batch normalization and max-pooling to progressively extract hierarchical features and reduce spatial dimensionality.

Hyperparameter	Value
Optimizer	Adam
Initial learning rate	1e-3 (with ReduceLROnPlateau)
Batch size	32
Epochs	24 (EarlyStopping used with patience 3)
Input size	128 x 128 (grayscale)
Loss	Categorical cross-entropy
Augmentation	Rotation ±15°, shift ±10%, zoom 10–15%, horizontal flip.
Callbacks	ReduceLROnPlateau, EarlyStopping.

Table 1. Model parameters.

Table 1. describes all the hyper parameters used in batch training of model. Data augmentation is applied to make dataset more robust and helps model in learning features effectively. Early stopping and learning rate reduction on plateau were used to improve generalization.

The full pipeline was implemented on T4 GPU of Google Colab notebook using TensorFlow and Keras for model development. The preprocessing parameters (CLAHE settings, morphological kernel sizes, ROI padding, and resizing dimensions) are documented for reproducibility.

Performance metrics are presented per-class and as overall summaries. The model is able to achieve the overall accuracy of 97%. The detailed classification report is given in Table 2, which includes the values of precision, recall, F1-score, and support for each class. The macro average and weighted average for all classes were the same, with values of 0.97 for precision, recall, and F1-score. These results show that the model gives consistent performance

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and can effectively classify different types of brain tumors with high accuracy and reliability on the testing dataset.

Class	**Precision**	**Recall**	**F1-score**	**Support**
Glioma	0.99	0.92	0.96	300
Meningioma	0.92	0.95	0.93	306
No tumor	1.00	1.00	1.00	405
Pituitary	0.96	0.99	0.98	300
Overall Accuracy	0.97			1311
Macro avg	0.97	0.97	0.97	1311
Weighted avg	0.97	0.97	0.97	1311

Table 2. Classification performance on Testing set.

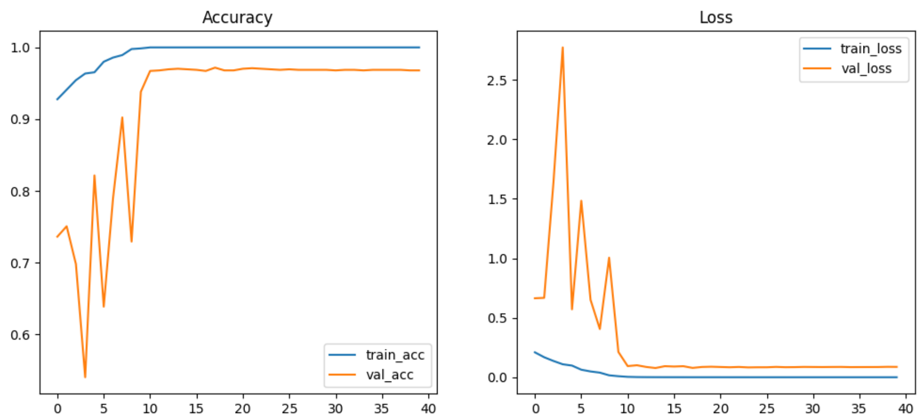

Fig 2. Model performance graph.

Above Fig 2. represents the accuracy and loss of the proposed CNN model over 40 epochs. From the accuracy graph, it can be seen that the training accuracy gradually increases and reaches almost 100%, while the validation accuracy also becomes stable around 97–98%, showing that the model has learned the features effectively without major overfitting. In the loss graph, both training and validation losses decrease rapidly within the first few epochs and later stabilize near zero, which indicates proper convergence of the model. These results confirm that the CNN model has successfully learned to classify MRI brain images into their respective tumor categories with high accuracy and good generalization.

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5 Conclusion and Future work

The ROI-based CNN achieved strong performance on the Testing set with an overall accuracy of 97% and per-class F1-scores above 0.90. The strongest class was the no-tumor category, and the model showed robust discrimination among tumor types after ROI preprocessing and augmentation.

Future work includes cross-validation, training with transfer learning and fine-tuning, external validation on other MRI datasets, and incorporation of multi-modal sequences and clinical metadata.

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