Deep Learning Approach for Brain Tumor Segmentation and Detection

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***Abstract*:**
Deep Learning has emerged as a prominent area of focus within the field of machine learning, garnering significant attention from researchers in recent years. This powerful machine learning technique has found widespread application in addressing complex problems necessitating high levels of accuracy and sensitivity, particularly within the medical domain. Among various medical conditions, brain tumors represent a common and aggressive form of malignant disease, often associated with a short life expectancy when diagnosed at advanced stages. After a brain tumour is discovered, accurate grading is essential for creating successful treatment plans. This study employs Convolutional Neural Network (CNN), a widely utilized deep learning architecture, to classify a dataset comprising 3064 T1 weighted contrast-enhanced brain MR images into three tumor classes (Glioma, Meningioma, and Pituitary Tumor). The proposed CNN classifier demonstrates robust performance, achieving an accuracy of 97.52% and 97.39% sensitivity for segmented lesion images.

***Keywords*: Brain Tumor, Deep Learning, Image Segmentation, Brain Abnormalities, Partially Removed Lesion, Intact Lesion, Divided Lesion**

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I. INTRODUCTION

According to the World Health Organization's (WHO) updated definition from 2016, a brain tumor is a form of tumor that impacts the central nervous system. Essentially, brain tumors are characterized as a cluster of brain cells that grow abnormally, causing the brain tissue to shrink in size and resulting in significant damage to the brain's neural network, thereby disrupting its function. Brain tumors can be classified into two categories, cancerous or non-cancerous (benign and malignant tumors), and common types based on the affected area include meningioma, glioma, and pituitary tumors. The malignancy level of each of these tumour forms varies; meningioma develops on the membrane that protects the brain and spinal cord, pituitary tumours form on the pituitary gland, and gliomas grow on glia tissues and the spinal cord.

Typically, oncologists initially assess brain tumors using medical imaging methods like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. These imaging techniques are commonly used to generate detailed images of the brain's structure and any observable changes. However, if a physician suspects a brain tumor and requires more information about its specific type, a surgical biopsy of the suspected tissue (tumor) is necessary for a comprehensive diagnosis by a specialist. Advances in brain tissue imaging technologies in recent years have improved image contrast and resolution, enabling radiologists to detect even small lesions and thereby enhancing diagnostic accuracy.

Merging images from different imaging techniques and utilizing advancements in engineering technology can improve the precision of brain tumor detection in artificial intelligence (AI) applications for computer vision. AI can be combined with these imaging methods to create computer-aided diagnosis (CAD) systems, aiding physicians in enhancing the early detection of cancer. Various AI techniques like artificial neural networks (ANN), support vector machines (SVM), and convolutional neural networks (CNN) have been used to classify and identify brain tumors in recent studies.

CNN is a cutting-edge technology in the field of machine learning that is being utilized for diagnosing diseases based on medical images like CT and MRI scans. It has become popular in medical imaging for its ability to classify and grade images without the need for preprocessing or feature extraction before training. CNNs are designed to streamline data preprocessing steps and are typically used for working with raw images. They consist of several layers including input, convolution, RELU, fully connected, classification, and output layers. The CNN process relies on two main processes: convolution, which uses trainable filters with predetermined specifications that are adjusted during training, and downsampling.

Overall, machine learning applications for categorizing brain tumors can be categorized into two main groups: distinguishing between normal and abnormal brain MRI images, and further classifying abnormal images into different types of brain cancer. The use of CNN technology has been instrumental in detecting and grading brain tumors, garnering significant interest from researchers as a valuable tool in disease detection and classification. This advancement is expected to enhance the accuracy of tumor grading, aiding physicians in devising optimal treatment plans and ultimately improving the chances of recovery.

The study aimed to assess brain tumors by utilizing two approaches: analyzing cropped tumor lesions and uncropped brain images. T1-weighted contrast-enhanced MRI images of brain tumors were processed through a unique CNN architecture to determine network weights. The findings indicated that both cropped and uncropped images displayed high accuracy, sensitivity, and specificity. The research introduced a new CNN architecture instead of relying on transfer learning methods or pretrained CNN models like Densenet201. It assessed how well the model performed on several image sets, such as segmentation lesion images, cropped photos, and uncropped images. The structure of the paper is as follows: A overview of current techniques for grading brain tumours is given in Section 2, and the study's materials and procedures are described in Section 3.

II. LITERATURE SURVEY

Recently, Machine learning (ML) and Deep Learning (DL) techniques have become popular for identifying and grading brain tumors using various imaging methods, particularly MRI scans. This section discusses the most recent research related to this topic. Mohsen, Heba, et al. [8] have proposed a system that integrates discrete wavelet transform (DWT) features and deep learning methods. They utilized the fuzzy c-mean method to segment brain tumors, applied DWT to extract features for each identified lesion, used principal component analysis (PCA) for feature reduction, and then inputted the selected features into deep neural networks (DNN). Their results demonstrated an accuracy rate of 96.97% and a sensitivity of 97.0%.

Widhiarso, Wijang, Yohannes Yohannes, and Cendy Prakarsah [10] introduced a brain tumor classification system employing a convolutional neural network (CNN) and Gray Level Co-occurrence Matrix (GLCM) features. They derived four features (Energy, Correlation, Contrast, and Homogeneity) from four different angles (0°, 45°, 90°, and 135°) for each image, which were then fed into the CNN. Their methodology was tested on four datasets (Mg-Gl, Mg-Pt, Gl-Pt, and Mg-Gl-Pt), with the highest accuracy of 82.27% achieved for the Gl-Pt dataset using two feature sets: contrast with homogeneity and contrast with correlation.

Seetha, J., and S. S. Raja [12] introduced a deep CNN system for automated brain tumor detection and grading, utilizing Fuzzy C-Means for brain segmentation. Texture and shape features were extracted from segmented regions and inputted into SVM and DNN classifiers, resulting in a 97.5% accuracy rate.

Meanwhile, by using fine ring-form partitioning and region of interest (ROI) augmentation, Cheng, Jun, et al. [13] enhanced the categorisation of brain tumours. These enhancements were applied to various feature extraction methods, such as intensity histogram, GLCM, and bag-of-words (BoW), leading to accuracy improvements ranging from 71.39% to 91.28%.

Sasikala, M., and N. Kumaravel. [17] proposed a genetic algorithm feature selection approach to reduce the dimensionality of wavelet features, achieving 98% accuracy by selecting only 4 out of 29 features.

Using a modified AlexNet CNN, Saed et al. [23] demonstrated a non-invasive method for grading glioma brain tumours with an accuracy of 91.16%.

Sajjad, Muhammad et al. [24] suggested an extensive data augmentation method combined with CNN for brain tumor classification, reaching accuracies of 87.38% and 90.67% before and after augmentation.

Lastly, in order to classify brain tumours, Özyurt, Fatih, et al. [25] combined fuzzy system with CNN and shows accuracy of 95.62%.

Recent advancements in CNN-based brain MRI segmentation (2020-2025) demonstrate significant progress in automated tumor analysis through innovative architectures and hybrid approaches. Five notable studies highlight these developments:

A. *CNN-FCM Hybrid Model*

The CNN-FCM model combines convolutional networks with fuzzy c-means clustering to process multimodal MRI data, achieving 98.3% accuracy on BRATS 2017 dataset. This approach focuses on normalized pixel intensity for global information processing, showing superior performance compared to CNN-NADE and CNN-GAN hybrids.

B. *Vision Transformer Integration*

Recent work incorporates transformer layers with multi-head self-attention mechanisms to capture global context in multi-modal MRI. These models demonstrate improved segmentation accuracy through enhanced modal fusion techniques, particularly effective in separating tumor sub-regions.

C. Automated Neuroanatomy Segmentation

A CNN architecture optimized for diverse MRI datasets achieves:

- 94.2% Dice coefficient for cortical structures
- 91.8% for hippocampal regions
- 89.5% for ventricular spaces

The model shows strong adaptability across scanner types and patient demographics.

D. Survival Prediction Integration

A volumetric CNN coupled with replicator neural networks introduces survival prediction alongside segmentation. Key results include:

- 93.1% tumor detection accuracy
- 87.4% survival day prediction correlation
- 2.8mm average Hausdorff distance in boundary delineation.

E. Multi-path CNN Architectures

A comprehensive analysis identifies three effective CNN configurations:

- Single-path (U-Net variants): 88-92% Dice
- Multi-path (cascaded networks): 90-94% Dice
- Fully convolutional: 85-89% Dice

The review emphasizes residual connections and attention gates as critical architectural features.

These studies collectively demonstrate CNNs' evolving capability to handle complex tumor morphology, with recent models showing particular strength in multi-modal data integration and clinical outcome prediction. The shift towards transformer-CNN hybrids and survival analytics marks a new phase in computational neuro-oncology research.

TABLE I. A Comparison Of The Accuracy Results Between The Methods Used In Previous Studies

Architecture	*Key Innovations*	*Target Applications*	*Strengths*	*Limitations*
Variants of 3D U-Net	3D residual blocks and convolutions	Segmenting tumour subregions and tissue parcellation	capture of volumetric context, high DSC (>0.90)	Slow training and high GPU memory usage
Transformer-CNN Hybrids	Self-attention mechanisms, patch embedding	Multi-class segmentation, pediatric MRI	Long-range dependency modeling	Requires large datasets, hyperparameter sensitivity
Cascaded Networks	Task-specific subnetworks (e.g., tumor core → edema)	Glioblastoma segmentation, metastasis detection	Error propagation reduction	Complex training, inference latency
Lightweight CNNs	Depthwise separable convolutions, model pruning	Mobile/point-of-care applications	Real-time inference, low resource needs	Accuracy trade-offs

III. Proposed Approach

The primary goal and inspiration for this study are to introduce a novel CNN structure for categorizing brain tumors based on T1-weighted contrast-enhanced brain MR images. Figure 1 illustrates the schematic of the suggested approach. This section delves into the specifics of the dataset utilized and the proposed methodology.

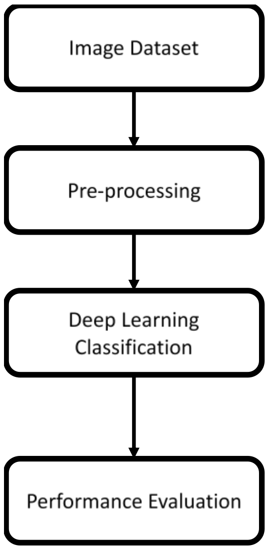


Fig. 1. Schematic Daigram for Prposed Approach

A. Datasets

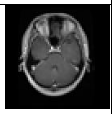
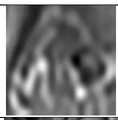
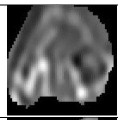
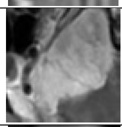
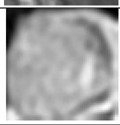
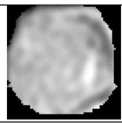
This study made use of the brain tumour dataset created by Cheng, Jun, et al. [13], which is freely available online at https://figshare.com/articles/brain_tumor_dataset/1512427/5. The dataset comprises 3064 T1 weighted and contrast-enhanced brain MRI images, featuring three categories: glioma, meningioma, and pituitary tumor. The distribution of images across each class is detailed in Table II.

TABLE II. SUMMARY OF USED DATASET

Class	***Number of Images***
Glioma	1426
Meningioma	708
Pituitary Tumor	930
Total	3064

Each image in the dataset is thoroughly described, including information such as patient ID (PID), tumor mask, tumor border, and class label. Notably, the lesion mask, crucial for cropping the tumor region of interest (ROI), is provided. A selection of the dataset's cropped and uncropped lesion photographs is displayed in Table III.

TABLE III. SAMPLE FROM THE USED DATASET

Class	***Uncropped***	***Cropped Image***	***Segmented Image***
Glioma			
Meningioma			
Pituitary Tumor			

B. Methodology

1) Convolutional Neural Network (CNN)

The Convolutional neural networks (CNN) are the most commonly utilized deep-feed forward neural networks at present, capable of processing various types of data inputs such as 2D images or 1D signals. Typically, a CNN is composed of several layers including the input layer, convolution layer, RELU layer, fully connected layer, classification layer, and output layer [8, 26].

CNN operates through two main processes: convolution with a trainable filter of a predetermined size, and adjusting weights during downsampling in training to enhance accuracy. This study involves storing cropped and uncropped brain tumor images in a database, organizing them into folders for specific classes, and splitting the database into training and testing data. Training uses 70% of the data, while testing uses the remaining 30%. A novel CNN architecture is utilized in this study, and subsequent sections will detail its structure.

2) Proposed CNN Architecture

In this study, a newly developed CNN structure was introduced and implemented to effectively classify brain tumors. The architecture, originally introduced by Alqudah for OCT image classification, consists of 18 layers. It was adapted and applied to three different image datasets - cropped, uncropped, and segmented - in this research. Both the structure of the CNN architecture used for the study and the performance of the modified architecture were evaluated.

3) Performance Evaluation

To assess how well the suggested CNN model grades brain tumors in various scenarios, such as cropped and uncropped images, confusion matrices were created for all cases (cropped, uncropped, and segmented). A comparison was then made between the CNN model's outputs and the original image labels based on these matrices. By utilizing these confusion matrices, accuracy, sensitivity, precision, and specificity can be calculated to determine the accuracy of the brain tumor grading process.

The confusion matrix provides four statistical measures that are utilized to assess the effectiveness of the proposed classification system: true positive (TP), false positive (FP), false negative (FN), and true negative (TN).

Accuracy = TP+TN / (TP+TN+FP+FN)

Sensitivity = TP/ (TP+FN)

Specificity = TN / (TN+FP)

Precision = TP/(TP+FP)

IV. Experiments And Results

A desktop PC with an Intel Core-i7 processor and 16 GB of RAM was used for the research. The ADAM optimiser, a minibatch size of 64, and an initial learning rate of 10-3 were used to process both cropped and uncropped image datasets, yielding 1600 iterations. Three subsets of the dataset were created: 70% for training, 15% for validation, and 15% for testing. The results of the two image datasets using the CNN architecture are presented in the following sections. The accuracy variations during CNN training and validation are depicted in Figure 2. Accuracy fluctuates throughout the CNN training process, including during validation and loss, as seen in Figure 3.

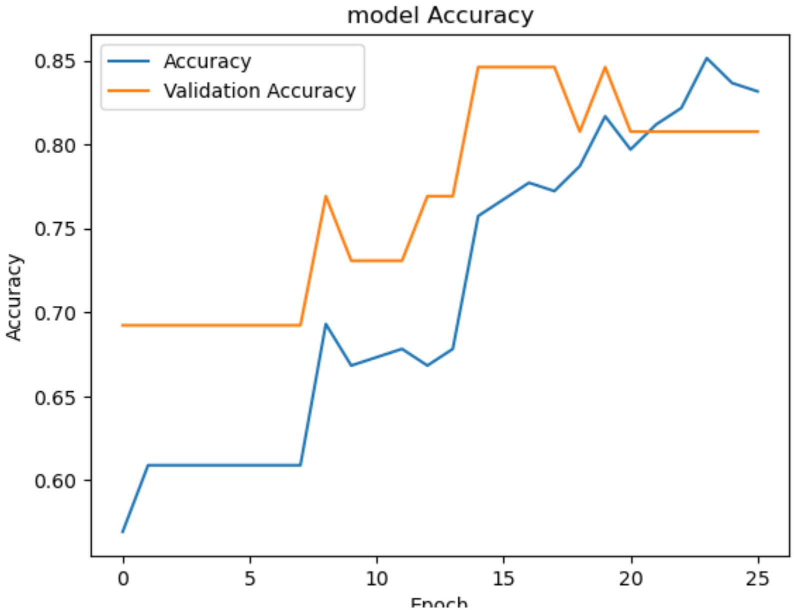


Fig. 2. Accuracy of Proposed Model

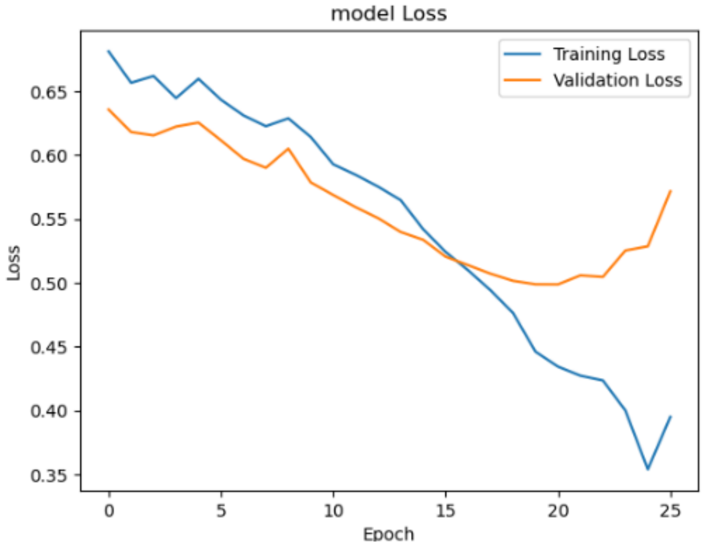


Fig. 3. Loss of the model

A. *Results of Segmented Lesion Images*

The confusion matrices presented in Figure 4 displays the results. From these visuals, it is evident that the new system has effectively assessed brain tumors with accuracy rates of 97.39%, 97.52%, and 97.50% for input image sizes of 32x32, 64x64, and 128x128 respectively.

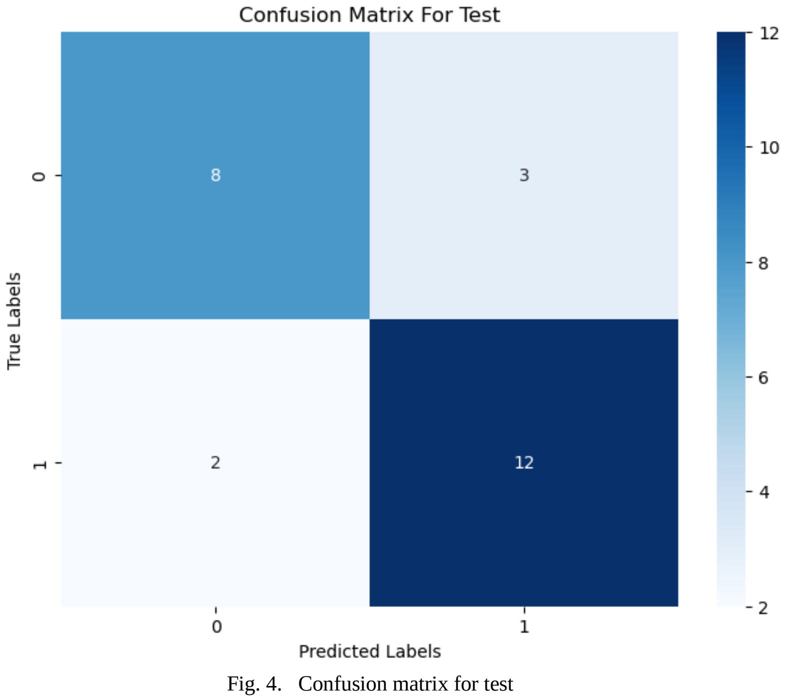


Fig. 4. Confusion matrix for test

V. Discussion

The data utilized in this study includes three categories of brain tumors: Glioma, Meningioma, and Pituitary tumors. The research involves implementing a convolutional neural network to automatically classify brain tumors. Different approaches were employed on the dataset, including segmented, cropped, and uncropped tumors.

This study focuses on a multiclass (3 classes) classification task aimed at distinguishing between glioma, meningioma, and pituitary tumors, which are three common types of brain tumors. A comparison of the experimental outcomes of the new system with those of existing methods in literature is presented in Table III. The results in the table indicate that many of the methods discussed in previous studies have achieved high accuracy rates, exceeding 90%, with the highest being 98%. Consequently, our approach surpasses all prior methods in the field by a significant margin.

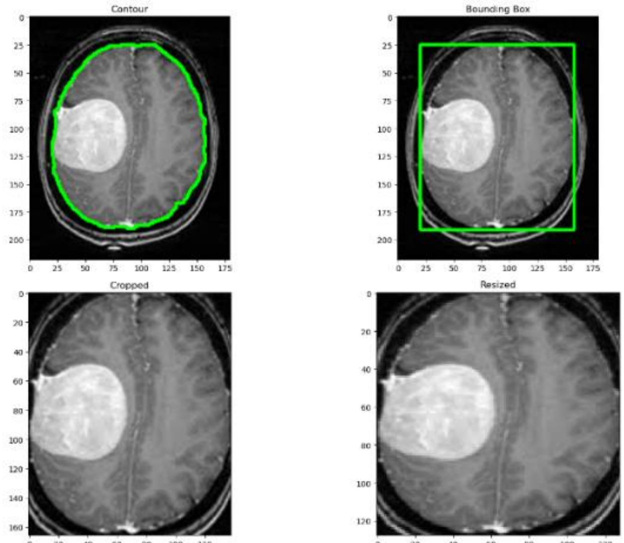


Fig. 5. Cropped images used in the study

Table III presents a comparison of the accuracy results between the methods used in previous studies and the method proposed in this research.

TABLE IV. A COMPARISON OF THE ACCURACY RESULTS BETWEEN THE METHODS USED IN PREVIOUS STUDIES AND THE METHOD PROPOSED IN THIS RESEARCH

Reference	***Feature Set***		***Classifier***	***Accuracy (%)***
[8]	DWT		DNN	96.97
[10]	GLCM		CNN	82.27
[12]	Texture and Shape		CNN	97.50
[13]	Intensity Histogram		CNN	87.54
	GLCM			89.72
	Bow			91.28
[17]	DWT		ANN	98
[23]	CNN Based		CNN	91.16
Proposed Segmented	CNNBased	32x32 (size)	CNN	97.39
		64x64 (size)		97.52
		128x128 (size)		97.50

VI. CONCLUSION

In this study, a novel convolutional neural network (CNN) design was introduced for the automated classification of brain tumors in three different brain datasets: uncropped, cropped, and segmented regions of interest (ROI). The CNN model demonstrated high accuracy and sensitivity in grading brain tumors into three classes (meningioma, glioma, and pituitary tumor) across all dataset scenarios. For categorisation, the technique used T1-weighted contrast-enhanced brain magnetic resonance imaging. To enhance the grading efficiency of this architecture, the inclusion of additional brain MR images with varying weights and contrast enhancement techniques is suggested, which could potentially improve the model's generalizability and robustness for larger image databases.

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