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ADVANCING BRAIN TUMOR DIAGNOSIS USING DEEP LEARNING AND AUTOMATED IMAGING TECHNIQUES

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Original Article

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Abstract

The study of tumor detection in brain is aimed for improvement of the required treatment for people that are suffering from brain tumor (BT). Brain tumors are aberrant cell evolutions in the brain, while cancer is an acronym employing to indicate tumors that are cancerous called malignant. CT or MRI investigations are used often to identify malignant regions in the brain. PET, cerebral arteriogram (CA), lumbar puncture (LP), and molecular testing (MT) can also be used to detect BTs. MRI scans are largely used in this investigation to examine the illness condition. The objectives of this study are to detect aberrant images and segment the tumor territory. The segmented mask can measure tumor density for therapeutic purposes.

Keywords: Brain Tumor, Deep Learning, Automated Image Techniques, CNN, Magnetic Resonance Imaging

Introduction

Brain tumors are divided into benign (noncancerous) and malignant (cancerous). Cells are replaced with fresh ones when they become damaged or old. Failure to remove damaged or old cells while creating new ones can lead to issues. When cells multiply, they produce a mass of tissue, known as a tumor. Because of the features such as the shape & size, region, and the kind of tumor in the brain, detecting them is extremely challenging. Early detection of brain cancers can be challenging due to inaccuracies in tumor size and resolution [1]. Early detection and treatment of tumors increase the patient's chances of successful therapy. Early tumor detection is crucial for effective treatment [4]-[5]. Brain tumors can be classified as either benign or malignant. For these people, an early and efficient diagnosis and treatment plan extends life expectancy and enhances quality of life. The Deep Neural Network is one of the most important and practical methods (DNN). MRI imaging gives reliable images of the brain, making it a crucial tool for detecting and evaluating neurological conditions. In the realm of medical detection systems (MDS) and MRI images are superior to computed tomography (CT) at detecting soft tissues in human brain. The proposed approach employs CNN to classify cancers in brain images. The main channel of a NN differs from a regular neural network (NN) in that it can extract features from images automatically and locally. Neural networks have learnable weights and biases [6]. The proposed approach can be improved based on the dataset's CNN findings. A machine learning algorithm is employed to extract features. The clustering approach was utilized on the data set, followed by applying the images to a CNN. The proposed approach was successful, as shown by the results. Extracting the property before applying to CNN prevents fatty lumps from being misconstrued for cancers, perhaps leading to medical errors. Performing attribute extraction prior to CNN application improves network accuracy.

Related Work

Several researchers are working on image processing approaches such as detection and extraction in many disciplines. Brain tumors are more advanced and hazardous, and screening them as early as feasible can save people's lives [2]-[3]. In [7], an automated approach is utilized to recognize and categorize the MRI imagery with super pixel classification. The ERT classifier is compared to SVM for classifying super pixels as tumors or normal. The ERT classifier approach performs well, as seen by the results. In [8], a CNN with 3 x 3 tiny kernels is utilized to automatically detect tumors. In [9], the AlexNet model CNN method for MS and normal tumors classifies 98.67% of images into three object classifications. In [10], a multi-stage FCM model developed is presented for segmenting brain tumors of medical MRI images. [11] Describes an efficient and successful classification and segmentation approach using CNNs. The suggested technique uses ImageNet to extract. The findings showed 97.5% classifier accuracy and 84% for segmentation accuracy. The researchers' analyzed multi-phase MRI images for provide tumor grading and compared deep learning structures to basic neural networks [12]. They discuss the current state of tumor identification and segmentation using deep learning models. Deep segmentation is achieved using 3D CNN, ANN, and SVM models. They used a neural network (NN) to segment pathological tissues (tumor), normal tissues such as WM and GM, and CSF, extract relevant features, and classify tumor images. According to [13], using data mining classification techniques can help discover tumors early on. The segmentation approach is automated and relies on CNN. According to this, tumor regions can be discovered by segmenting MRI images. Radiological exams assist in identifying tumor size and location. Manual segmentation is a time-consuming process. Preprocessing was made with ADFs (anisotropic diffusion filters). SVM has been used for classification. It presents a unique technique based on isolated local squares. The suggested method for brain tumor segmentation includes super pixel separation, model building and feature extraction.

The key research gaps finding in the literature survey are: the use of deep learning and automated imaging are being used to advance brain tumor detection, however there are significant research gaps that require attention. The lack of big, annotated, and diversified datasets impedes successful model training, necessitating collaborative efforts to provide complete, multi-institutional resources. Furthermore, the absence of understandable AI (XAI) tools makes it difficult for physicians to place confidence in and comprehend DL results, emphasizing the importance of transparency through methods such as saliency maps. Models trained on small populations fail to generalize, require the incorporation of transfer learning with varied information to decrease bias, and enhance accuracy. Another problem is the combination of multifunctional imagery (MRI, CT, PET), which necessitates the creation of models capable of efficiently processing and combining these disparate information sources. Early identification and precise tumor subdivision remain challenging, but radiomics and deep learning integration may increase their precision.

Substantial gaps are found in clinical incorporation, as DL systems must smoothly integrate into established medical workflows while providing user-friendly interfaces. Longitudinal models are also required to predict tumor growth and treatment outcomes. Addressing data privacy concerns through federated learning and encryption is critical, as is developing models that are robust to noisy or artifact-laden pictures. Finally, improving computational models such as DL models for real-time, affordable options, particularly in resource-constrained environments, will be important for wider clinical application. Closing these gaps would greatly enhance the accuracy, speed, and customization of BT diagnosis.

Automated imaging techniques aims to improve the accurateness, effectiveness, approachability of brain tumor exposure and diagnosis by combining advanced AI methods and imaging technologies. Especially, the purpose of detecting brain tumors with Convolutional Neural Networks (CNNs) is to automatically identify and classify tumors in the brain from medical imaging data, such as MRI or CT scans. This technique intends to help healthcare workers diagnose brain tumors more quickly, correctly, and efficiently, thereby improving patient outcomes. The specific objectives are listed below: The key objectives include:

- Improving Diagnostic Accuracy: Use deep learning models (such as CNNs) to evaluate complicated patterns in medical images more precisely than previous methods. As a result, misdiagnoses are reduced, allowing for more accurate identification of tumor types, grades, and stages.
- Automate Tumor Detection and Analysis: Automate the process of finding and analyzing brain tumors from medical imaging data (MRI, CT scans, etc.), minimizing the reliance on manual, human-driven picture interpretation. It leads to speedier diagnosis and fewer human errors, which is especially significant in critical medical situations.

- Early Diagnosis and Detection: Create deep learning models that can identify brain cancers early on, even if they are tiny or undetectable, to enable timely treatment and better patient outcomes. Thus, better treatment planning and early intervention lead to higher survival rates.
- Improving Tumor Segmentation and Quantification: To quantify features like size, shape, and location, isolate the tumor from surrounding brain tissues using sophisticated deep learning techniques. This allows for exact tumor segmentation. It helps improve treatment decision-making and monitoring by providing precise tracking of tumor growth or shrinking over time.
- Integration of Multimodal Imaging Data: To improve diagnostic precision and treatment planning, use multimodal imaging data (such as combining MRI, PET, and CT scans) to provide a more thorough examination of brain tumors. It improves the interpretation of difficult instances where information from a single imaging modality may not be sufficient for a precise diagnosis.
- Quicker Healthcare Provider Decision-Making: Use deep learning models that can swiftly and effectively process big datasets to speed up the tumor identification and classification process. It improved patient care, quicker treatment planning, and a shorter period between diagnosis and therapy.
- Offering Second Opinions and Reducing Human mistake: Reduce the possibility of human mistake in brain tumor diagnosis by using deep learning models as decision support tools that provide radiologists and doctors with second opinions. With AI-supported suggestions to complement medical professionals' knowledge, it enhanced clinical decision-making.
- Customizing Therapy Plans: Use deep learning models in conjunction with imaging data analysis to offer insights into tumor behavior, genetic traits, and therapy response. This makes it possible to create more individualized treatment programs. The customized therapy plans that minimize side effects and increase treatment success are based on the features of the tumor.
- Lowering Healthcare Costs and Increasing Accessibility: Create AI systems that can be used in underserved or low-resource areas to make brain tumor diagnosis more broadly available, which will ease the strain on medical professionals and healthcare systems. It increases the affordability and accessibility of cutting-edge diagnostic technologies for a wider population, particularly in poor or isolated locations.
- Facilitating Long-Term Monitoring and Follow-Up: Use deep learning models to track tumor size, growth, and response to treatment over time by automatically analyzing follow-up scans. This will allow for long-term monitoring of patients with brain tumors. Patients with brain tumors should be effectively and continuously monitored in order to modify treatment regimens and take appropriate action as needed, lowering the chance of metastasis or recurrence.
- Enhancing Knowledge and Research on Brain Tumors: Learn more about the biology, behavior, and possible biomarkers of brain tumors by using deep learning and automated imaging to find patterns and insights in massive image datasets. It assists in the discovery of new medicines or therapies for patients with brain tumors.

To transform the detection, diagnosis, and treatment of brain cancers, deep learning and automated imaging techniques are being used to advance brain tumor diagnosis. With the potential to greatly enhance patient outcomes, these goals center on boosting accessibility and affordability, improving diagnostic accuracy, speeding up and streamlining the process, and customizing treatment programs.

Proposed Method

Figure 1 illustrates the design of the proposed system. The suggested system's block diagram shows four major stages: preprocessing, segmentation, feature extraction, and classification. Initially, brain MRI images are preprocessed to improve image quality and reduce noise. The next stage is segmentation, which isolates the tumor region. Following that, feature extraction is performed, which involves identifying significant tumor characteristics. Finally, the retrieved features are applied to the classification step to assess the presence and kind of tumor.

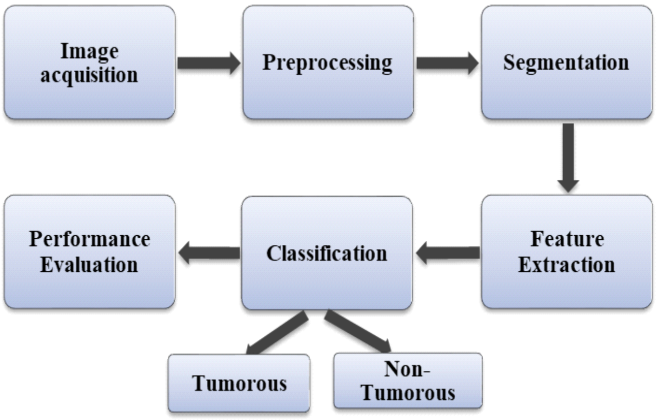

Fig. 1. Design flow of BT Diagnosis

Image Acquisition

Brain tumor detection can be studied using several biomedical imaging records. Conventional approaches include CT, MRI. Brain tumors can also be detected via PET, cerebral-arteriogram (CA), lumbar puncture (LP), and molecular testing (MT). The MRI dataset published to Kaggle public website, which considered 1531 normal brain images and 656 aberrant ones.The augmentation procedure is also used to boost the sample count. The total collection consists of 656 normal and 1531 aberrant images.

In this stage is intended to prepare brain pictures for advance handling [13]. This practice is heavily reliant on the data collecting equipment, which has its own inherent characteristics. Converting 3D raw data to grayscale or 2D is necessary. Median filtering is ideal for reducing noise in biomedical imaging applications. The dataset includes photos with varying resolutions. Throughout the enhancement process, every image is rotated and scaled to a standard size. Histogram equalization increases image quality. The photos are improved using a contrast-limited adaptive histogram equalization method.

Image Segmentation

A specified portion of the image is being separated from its background. This stage is largely used for feature extraction. Disease segmentation is based on simple thresholding and morphological processes like erosion, dilatation, and opening. However, segmenting brain tumor images at this level yields insufficient information about the tumor regions. The healthy photos have the same intensity as the tumor location. The segmentation process is capable of separating the skull of the brain. This Region of Interest (ROI) contains the tumor. The OTSU-based thresholding technique creates a segmented mask of the skull [14][15].The enclosed region's boundary is created using the active contour approach. A second stage of segmentation can be applied to the ROI to generate a mask of the tumor location. This method may not yield satisfactory results in healthy images.

Feature Extraction

Analyzing actual aspects can reveal disease behavior or symptoms. Feature selection plays a significant role in classification. Common characteristics include asymmetry, diameter, and border irregularity

Classification

Various machine learning algorithms are being used to detect diseases in brain images. ANNs can be used to categorize if features are mined in a specific order [16][17]. An ANN classifier adopts a single feature that is unrelated to any other features. Deep learning approaches are efficient for classifying tumor images without segmentation. The Convolutional neural network technique may generate deep neural networks. Figure 6 shows the general architecture of convolutional neural networks.

A reduction in dimension is required to begin training. The feature dimension is sampled down at the pooling layer. Fully connected layers adjust the score for each label. Softmax layers organize the model using feature and class scores. The CNN architecture is slightly changed to train brain tumor images.

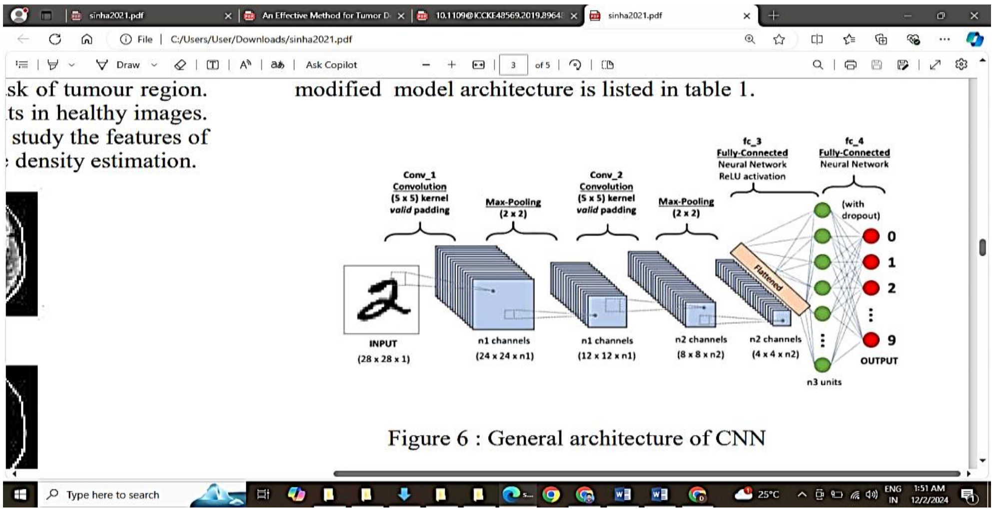

Fig. 2. Overview of the general architecture of a Convolutional Neural Network (CNN)

Algorithms for proposed methodology is as mention below:

Start with image acquisition.

- The input is: MRI Brain Imagery (Normal and Abnormal)
- Data The source: Kaggle Dataset (1531 aberrant and 656 normal)

Stage One: Preprocessing

- Convert the images from 3D raw to greyscale/2D.
- Use median filtering to minimize noise.
- Image Augmentation (rotation and scaling to standard format).
- HE for Image Enhancement and CLAHE

Stage Two: Segmentation

- Thresholding method: OTSU-based thresholding
- Extract Region of Interest (ROI): Skull and Tumor Area
- Active Contour Method: Determining Malignant Regions
- Output: Segmented mask of the tumor area.

Stage Three: Feature Extraction

- Determine tumor features (inequalities, size, and boundary abnormality).
- Retrieve the required characteristics for categorization.

Stage Four: Classification

- Apply Convolutional Neural Network (CNN) for classification
- CNN Architecture:
- Input layer: Preprocessed images
- Convolution layers: Feature extraction
- Pooling layers: Reduce dimension
- Fully connected layers: Adjust classification scores
- Softmax layer: Final classification result (normal/abnormal)

Stage Five: End: Tumor Diagnosis and Classification

- Output: Diagnosis (presence and type of brain tumor)

Results and Discussion

Brain tumors are detected in MRI pictures utilizing a variety of imaging modalities routinely used in medical diagnosis. Brain tumor MRI pictures are first collected from a database. These photos frequently contain noise and low contrast, preventing accurate analysis. The image is pre-processed with a median filter to improve its quality by reducing noise and increasing contrast. The figure depicts the result of the filtering procedure. The improved image shows both the aberrant tumor tissue and the surrounding normal tissue. To efficiently separate and extract the tumor, post-processing processes such as segmentation and classification are used. A genetic algorithm is used to segment the test image and optimize it.

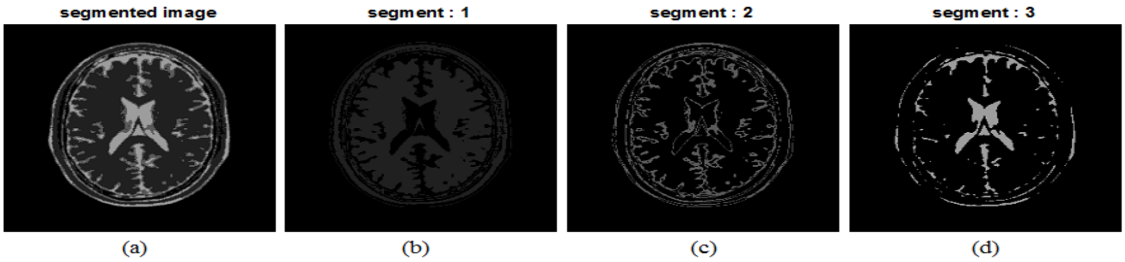

Fig. 3.Segmentation results of normal brain T2-W MRI image showing (a) segmented image, (b) gray matter (GM), (c) white matter (WM) and (d) cerebrospinal fluid (CSF).

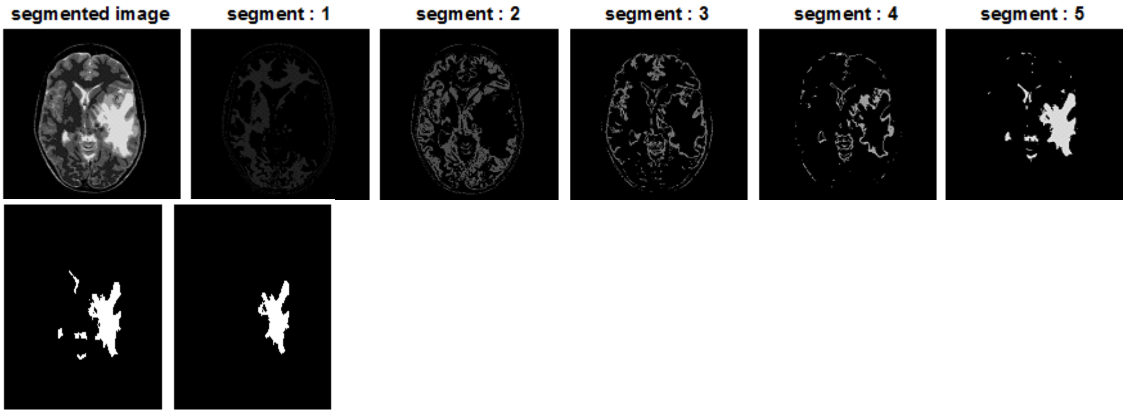

Fig.4. Multiple segmentation results of abnormal brain T2-W MRI image showing GM, WM, CSF, outlier of tumor called edema and extracted tumor.

Table 1. Confusion matrix defining TP, TN, FP and FN and various performance parameters

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

In this context, we describe some features using simple notations such as TP=S, TN=T, FP=U, and FN=V, where TP denotes True Positive, TN denotes True Negative, FP represents False Positive, and FN represents False Negative.

- True Positive (TP): This feature indicates that an abnormality in the brain has been accurately diagnosed.
- True Negative (TN): It indicates that the brain correctly recognizes normal.
- False Positive (FP): It refers to the mistaken identification of normal brain function as abnormal.

- False Negative (FN): A disorder in the brain that was mistakenly identified as normal.

From the table 1, the performance parameters are identified as from equation (1) to (3)

Accuracy = (S+T)/(S+T+U+V) ---------------- (1)

Sensitivity = (S)/(S+V) -------------------------- (2)

Specificity = (T)/(T+U) -------------------------- (3)

Here experimented results observed as S=TP=1520, U=FP=32, T=TN=680, V=FN=12.

Accuracy = 98.03%

Sensitivity = 99.12%

Specificity = 95.50%

Therefore, obtained performance are accuracy is 98.03%, sensitivity is 99.12% and specificity is 95.5% which are better than the existing. When compared to current methodologies, the experimental results in this study show a considerable improvement in performance. With a remarkable accuracy of 98.03%, the model was able to accurately categorize the majority of occurrences, with TP of 1520, FP of 32, TN of 680, and FN of 12. The model's outstanding ability to detect positive cases while reducing false negatives is demonstrated by its 99.12% sensitivity. This implies that there are relatively few missed cases and that the model is quite good at identifying genuine positives. Furthermore, the model's remarkable capacity to accurately detect negative situations while lowering false positives is demonstrated by its 95.5% specificity. These findings drove the prevailing techniques, which has an accuracy of 93.26%, sensitivity of 99.21%, and specificity of 97.98%. The suggested model's better performance in terms of accuracy, sensitivity, and specificity reveals its superior ability to effectively categorize both positive and negative cases. This advancement could lead to better results in real-world applications that require precise data classification. As a result, the findings support the proposed approach's efficacy and potential for wider application in relevant sectors.

The table 2 presents the accuracy achieved by different techniques in comparison to the proposed method.

Table 2: Comparison of different methods of classification

Technique attempted by	Accuracy
Narayana [1]	93.26%
Rajani [13]	89.02%
Sinha [14]	92.01%
Narayana [5]	93.33%
Proposed	98.05%

As indicated in the table 2, the proposed method's accuracy of 98.05% exceeds the other strategies investigated in this study. The approaches of Narayana [1] and Narayana [5] attained accuracy rates of 93.26% and 93.33%, respectively, while Rajani [13] and Sinha [14] reported lower accuracy values of 89.02% and 92.01%. The proposed technique shows a significant improvement, indicating its effectiveness when compared to existing approaches. This increase in accuracy indicates that the proposed method is more reliable and efficient in achieving proper classifications, making it a promising solution for the problem at hand.

Conclusion

This article describes a deep learning-based strategy for detecting brain tumors. Early identification of cancer enables timelier and better therapy. The Kaggle dataset provides high-quality MRI images that are appropriate for research purposes. Several segmentation algorithms were evaluated. The most effective methods for this dataset are multilayer threshold and OTSU threshold. The improved Convolutional Neural Network technique achieved a 98% accuracy rate. A density estimation approach using the Gaussian kernel distribution is proposed. This system could be enhanced with a web interface. MRI can detect a range of ailments. Aside from density, other factors may be evaluated for therapeutic purposes.

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