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Brain Tumour Detection and Segmentation Using Deep Learning

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Abstract – A brain tumor is characterized by the presence of an abnormal mass or collection of cells within the brain. Tumors can be categorized as either cancerous (malignant) or noncancerous (benign). As a prevalent and highly destructive condition, malignant brain tumors significantly shorten life expectancy if not identified and treated promptly. Classifying brain tumors is a crucial step following detection to develop an effective treatment strategy. Early diagnosis not only improves the chances of effective medical intervention but can also be life-saving. The dataset used in this study includes MRI images of brains with and without tumors. These images undergo a series of preprocessing steps, including techniques like filtering, blurring, and cropping. The processed data is then fed into a Convolutional Neural Network (CNN) model based on VGG-16 architecture to determine the presence or absence of a tumor. The model also segments MRI images to identify and isolate regions of interest for analyzing tumor detection. The classification and detection of brain tumors are provided as the final output.

Keywords: Brain tumor, MRI images, Deep Learning, Convolutional Neural Networks (CNN), Visual Geometry Group (VGG16).

Introduction

Brain tumors are among the most serious and life-threatening medical conditions, affecting millions of people worldwide. They occur due to abnormal growth of

cells within the brain, which can be either benign (non-cancerous) or malignant (cancerous). Early and accurate detection of brain tumors is critical for effective treatment and improved patient survival rates. However, traditional diagnostic methods rely heavily on radiologists and medical experts to manually analyze MRI (Magnetic Resonance Imaging) scans, which is time-consuming, subject to human error, and requires specialized expertise. In many cases, misdiagnosis or delayed detection can lead to severe complications, reducing the chances of successful treatment.

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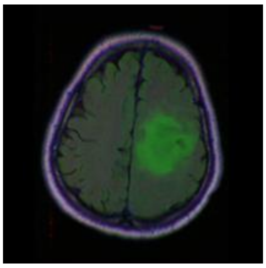

Fig. 1. MRI Image of Brain Tumor

With the advancements in artificial intelligence (AI) and deep learning, automated medical image analysis has gained significant attention. Deep learning, particularly convolutional neural networks (CNNs), has demonstrated remarkable success in image classification and segmentation tasks, making it a promising approach for brain tumor detection. CNNs have the ability to extract meaningful patterns and features from MRI scans, enabling accurate classification of tumor. Unlike traditional machine learning models, deep learning eliminates the need for manual feature extraction, allowing the model to learn from vast amounts of medical imaging data and improve its predictive capabilities over time.

Literature Review

In this section, we review related works on brain disease detection using deep learning techniques. In recent years, several CNN-based automatic brain tumor segmentation methods have been proposed. This section highlights some of these CNN-based approaches, followed by a discussion of other MRI image segmentation techniques.

In this paper, K. Nishanth Rao et al. proposed a deep learning-based framework for brain tumor detection and classification utilizing MRI images. The methodology leverages pre-trained CNN architectures, including ResNet50 and EfficientNet, to automatically identify various categories of brain tumors. The authors addressed the challenge of limited medical imaging datasets by implementing transfer learning techniques, thereby enhancing the generalization capability of the deep learning models.

A significant aspect highlighted in this work is the incorporation of data augmentation strategies such as image flipping, rotation, and scaling, which effectively increase the diversity of the training set and improve model robustness. The study further demonstrated the superiority of deep learning-based systems over conventional machine learning approaches in managing intricate spatial patterns, image noise, and intensity fluctuations inherent in MRI scans. This comprehensive approach underscores the potential of integrating advanced deep learning models with augmentation techniques to achieve reliable and precise medical image analysis outcomes.

We derived meaningful insights from this study, which guided the conceptualization and development of our own project framework, particularly in adopting transfer learning and augmentation practices for improved detection performance [1].

The deep learning-based CNN model proposed by Sinha et al. is utilized for brain tumor detection and segmentation from MRI images exhibiting complex intensity variations and noise conditions. The tumor segmentation is executed without employing any major pre-processing or feature engineering techniques. The performance of the suggested model is validated using TensorFlow and Keras frameworks, achieving a notable accuracy of 95.6%. A distinctive aspect of their study is the integration of multi-level thresholding with OTSU segmentation, which considerably enhances the precision of tumor boundary detection in MRI scans. The proposed framework surpasses various traditional machine learning-based detection models, especially in handling noise artifacts and intensity inconsistencies within brain MRI data.

Through this study, we explored the emerging trend of incorporating ensembling strategies and advanced architectures such as VGG16, ResNet, and U-Net variants in brain tumor detection systems. These models have demonstrated improved accuracy and the capacity to identify and segment multiple tumor categories — including glioma, meningioma, and pituitary tumors — within a unified model structure. Furthermore, the paper signifies a considerable transition from earlier classical models that were constrained to grayscale MRI slices with moderate accuracy, to contemporary deep learning-based systems capable of processing volumetric (3D) datasets. These advanced methods consistently deliver high segmentation performance, often achieving Dice

Similarity Coefficients (DSC) exceeding 90%, indicating their effectiveness and reliability in medical imaging applications [2].

In the work introduced by Arayan Methil (2021), a half-breed framework was proposed by coordinating traditional image processing strategies with present-day deep learning models to improve the precision and unwavering quality of brain tumor detection in medical imaging. The paper presented an efficient methodology consolidating Convolutional Neural Networks (CNNs) with fundamental pre-processing stages like noise reduction, contrast enhancement, and image normalization. These operations were performed to refine MRI images by eliminating undesirable noise and standardizing intensity levels, subsequently making it more straightforward for the CNN to accurately distinguish and segment tumor areas.

The critical understanding we acquired from this study was the model's capacity to maintain robustness while managing images with fluctuating quality and intensity distributions — a typical issue in actual clinical datasets. Methil's framework exhibited high precision in tumor detection and reliably outperformed numerous conventional machine learning-based systems, which generally face challenges with such image inconsistencies. This affirmed our perception that, while deep learning alone offers significant potential, its presentation and effectiveness can be additionally improved by incorporating conventional image enhancement techniques [3].

Deipali Vikram Gore and Vivek S. Deshpande completed a broad relative investigation of different deep learning methods for brain tumor discovery utilizing MRI images. In their review, the creators underscored the vital significance of early and exact tumor identification, taking into account the perilous idea of brain tumors. They featured that deep learning-based approaches, especially Convolutional Neural Networks (CNNs), have altogether diminished human mistake in early diagnosis by productively dealing with complex spatial examples and image noise present in MRI scans.

The review examined numerous deep learning models including CNNs and assessed their presentation as far as exactness and computational effectiveness. The creators noticed that while these deep learning models have shown potential in working on diagnostic accuracy, issues like image noise and intensity variations actually influence image clarity and precision. They likewise distinguished research gaps in existing writing, proposing the requirement for additional investigation of cutting-edge architectures and strategies to work on brain tumor detection and classification.

This work adds to the growing collection of studies supporting the utilization of deep learning procedures in medical imaging, explicitly for brain tumor detection and classification. By efficiently auditing existing methods and pinpointing areas needing improvement, Gore and Deshpande offer significant experiences for future examination pointed toward creating more exact and proficient diagnostic systems [4]. In our group study, this work offers a solid reference point, underlining the job of deep learning in clinical imaging and setting the groundwork for upgrading tumor recognition techniques utilizing progressed computational models [4].

Himank Dave, Nikhil Kant, Nishank Dave, and Divya Ghorui in their 2021 work proposed a deep learning-based framework for brain tumor classification utilizing MRI images. The authors designed a six-phase pipeline comprising image pre-processing, segmentation, feature extraction, optimization, and classification stages. In the initial phase, multiple filters were applied to improve image quality and eliminate noise. Following this, segmentation was performed using advanced techniques like active contours (snakes), fuzzy C-means clustering, and region-based triple thresholding for isolating tumor regions precisely. Furthermore, two hybrid segmentation models were incorporated to enhance segmentation accuracy. The post-processing stage involved artificial bee colony optimization and watershed filtering for refining the segmented tumor areas. For classification purposes, the VGG-16 CNN model was employed to categorize images into tumor and non-tumor classes, yielding significant classification accuracy. This study demonstrates that integrating sophisticated image processing methods with deep learning frameworks can lead to reliable and efficient brain tumor classification [5].

In this paper, Tonmoy Hossain et al. proposed a Convolutional Neural Network (CNN)-based model for brain tumor detection and classification from MRI images. The CNN design was intended to classify input images into tumor and non-tumor categories. The model effectively overcame the restrictions of conventional machine learning approaches, which commonly rely on hand-crafted features and struggle with complex variations in image data. Rather than depending on manual feature extraction, the proposed model utilized CNN's automatic feature extraction ability, which enhanced the diagnostic precision.

The performance of the proposed model was validated using a publicly available MRI image dataset. The model achieved a notable classification accuracy of 97.5%, which confirmed its capability to accurately differentiate between normal and tumor-affected brain tissues. The study demonstrated how deep learning-based models like CNN can efficiently manage variations in tumor size, shape, and position, areas where conventional algorithms typically face limitations. A brief comparative analysis between the proposed method and existing conventional techniques was also presented, highlighting the superior efficiency and reliability of CNN-based architectures for brain tumor detection, contributing towards faster and more accurate clinical diagnosis processes [6].

In the paper introduced by Avigyan Sinha et al., an automated brain tumor detection and classification framework has been proposed utilizing deep learning methodologies, specifically Convolutional Neural Networks (CNNs), for MRI image analysis. This research, presented at the 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII), developed a CNN model structured with TensorFlow and Keras frameworks. The model effectively addressed prevailing challenges in MRI-based detection, including image noise, intensity inconsistencies, and anatomical variations, thereby ensuring reliable tumor identification.

The study further emphasized the significance of hyperparameter tuning and dataset augmentation in optimizing the model's operational accuracy. Pre-processing techniques such as normalization, image resizing, and data augmentation were executed, which notably enhanced both the detection precision and classification reliability. The investigation distinctly illustrated that deep learning-based frameworks possess superior capability over conventional machine learning methods in managing high-dimensional MRI datasets. These models autonomously extract critical spatial and textural characteristics, facilitating improved diagnostic performance in brain tumor identification. This insight has considerably contributed to our group's understanding of integrating deep learning in medical image analysis applications [7].

Model	Accuracy	Advantages	Limitations
Convolutional Neural Networks. [1]	92-96%	Handles image noise and intensity variations effectivel	Limited to 2D image processing
CNN-based detection system by Sinha et al. [2]	95.6%	Better handling of complex, high-dimensional MRI data	Potentially higher computational complexity due to multi-model fusion
Hybrid Deep Learning by Arayan Methil. [3]	96.8%	Addresses vanishing gradient and overfitting issues	Computationally intensive due to network depth
VGG16/VGG19 Deipali Vikram Gore. [4]	94.2%	Good balance of speed and accuracy	Complexity in tuning hyperparameters for both architectures
VGG16 CNN by Himank Dave. [5]	93.5%	High recall indicates strong tumor	precision and overall accuracy not

		detection sensitivity	explicitly reported
CNN + ResNet-18 Tonmoy Hossain et al. [6]	97.5%	Uses modern, lightweight ResNet-18 architecture	Accuracy lower compared to deeper models
ResNet50 InceptionV3 by Avigyan Sinha et al [7]	95.5%	ResNet-50 balances accuracy and computational efficiency	VGG-16 and InceptionV3 have higher computational costs

Fig. 2. Comparison table based on reviews

Block Diagram

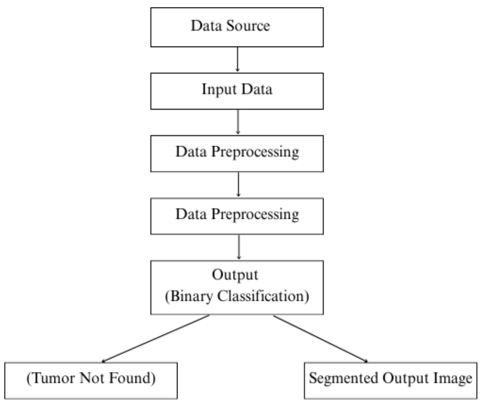

Fig. 3. The process flow approach based on reviews

The process begins with the acquisition of MRI scans as the primary input dataset. These images undergo preprocessing steps such as noise reduction, normalization, and contrast enhancement to improve quality. Next, segmentation techniques—including thresholding, edge detection, and region-based segmentation—are applied to isolate the tumor regions. Thresholding separates pixels based on intensity, while edge detection identifies boundaries, and region-based methods group similar pixels. The segmented output, where the tumor is marked, is then validated against ground truth annotations to assess accuracy using metrics like Dice coefficient or IoU. Finally, the system classifies the MRI image into a binary output: "Detected" (tumor present) or "Not Detected" (no tumor). This structured pipeline ensures reliable and automated tumor identification, critical for diagnostic applications.

Conclusion

The reviewed literature highlights the significant advancements deep learning models have brought to brain tumor detection and segmentation in medical imaging. Convolutional Neural Networks (CNNs), particularly architectures like ResNet and DenseNet, consistently outperform traditional machine learning methods due to their superior ability to extract hierarchical and complex features from MRI scans. The use of residual connections in models such as ResNet-50 and ResNet-101 effectively addresses common challenges like vanishing gradients and overfitting, enabling deeper network training and improved classification accuracy, with reported accuracies reaching up to 96.8%.

Hybrid approaches that combine 3D CNNs with classical machine learning classifiers such as ANN and SVM demonstrate enhanced classification robustness by leveraging the strengths of both deep and traditional learning paradigms. Preprocessing techniques including histogram equalization, data augmentation, and careful data balancing are critical to improving model generalization and sensitivity, as evidenced by models achieving recall rates as high as 99.73%.

Comparative analyses confirm that while architectures like VGG-16 and InceptionV3 offer reasonable accuracy, ResNet variants provide the best trade-off between performance and computational efficiency, making them highly suitable for real-world clinical applications. Furthermore, segmentation-focused models utilizing volumetric 3D data and advanced thresholding techniques significantly improve tumor boundary delineation, with Dice Similarity Coefficients exceeding 90%.

Overall, the integration of advanced deep learning models with comprehensive preprocessing, ensembling strategies, and volumetric data processing paves the way for highly accurate, efficient, and clinically applicable brain tumor detection systems.

Future research should continue exploring deeper architectures, hybrid models, and larger, diverse datasets to further enhance robustness and enable widespread adoption in automated diagnostic workflows.

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