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Brain Tumor Detection Using Deep Learning

[1]Astha Singh, [2]Richa Sahu, [3]Devesh Kumar Baghel, [4]Ms. Prapti Pandey

[1]Computer Science and Engineering Shri Shankaracharya Institute of Professional Management and Technology, Raipur

[2]Computer Science and Engineering Shri Shankaracharya Institute of Professional Management and Technology, Raipur

[3]Computer Science and Engineering Shri Shankaracharya Institute of Professional Management and Technology, Raipur

4Assistant Professor Computer Science and Engineering Shri Shankaracharya Institute of Professional Management and Technology, Raipur

Abstract: Recent studies on utilizing deep learning (DL) algorithms for the identification of brain tumors have focused primarily on gliomas (tumors arising from glial cells), meningiomas (tumors of the meninges), and pituitary tumor types (tumors of the pituitary gland) with a variety of different approaches. Convolutional neural networks (CNNs) and hybrid architectures will be investigated in the detection and classification of tumors within magnetic resonance imaging (MRI) scans at an early stage of disease progression. The proposed work will utilize the concepts of transfer learning by employing pretrained CNN architectures, such as YOLOv7, VGG16, and ResNet as well as methods for enhancing DL accuracy, such as convolutional block attention modules (CBAM), and explainable artificial intelligence (EAI) techniques (such as Grad- CAM) as tools to achieve high degrees of tumor detection accuracy (>95- 99%) and generate clinically applicable heat maps that can assist clinicians in performing diagnostic tasks. Following the detection of a tumor, each individual will receive a tailored evidence-based precaution model to assist them in monitoring their health by developing personalized recommendations that will outline how to track their symptoms based on their specific type of tumor (e.g., symptom tracking for gliomas, imaging frequency for meningiomas, hormonal testing for pituitary tumors).

Key methodologies utilized in the study include the following:

- DL automates the extraction of features from MRIs while providing a diagnostic support (DS) solution to facilitate treatment planning following tumor detection.

- The researchers developed multiple different types of CNNs combined with the YOLO model for the purpose of developing a model for tumor skin identification while also developing an ensemble model using machine learning or rule-based approaches based on the specific tumor classification to generate precautionary recommendations based on the characteristics of the tumor.

Keywords: BrainTumor, Convolutional neural network, Machine learning, MR

Introduction

Brain tumors are considered one of the most life-threatening medical conditions. They occur when cells in the brain or central spinal canal grow in an abnormal and uncontrolled manner, exceeding the normal boundaries of healthy tissue. These tumors may be classified as non-cancerous or cancerous, and both types can pose significant risks, including neurological dysfunction, cognitive deficiency, seizure activity, and the possibility of death if not treated adequately. Based on the differences in histological types, brain tumors are considered heterogeneous and therefore create difficulties for diagnosis / therapeutic decision making, as each one grows differently, is found in a different location, and has a different prognosis.

To treat brain tumors effectively, it is very important to detect the tumor in an early and accurate manner, as early diagnosis allows clinicians to perform the necessary intervention in time, either through surgical removal, radiation therapy, chemotherapy, or by using a combination of the above therapies. This results in maximal effectiveness of treatment and minimal neurological damage. Unfortunately, due to insidious onset of symptoms and the lack of specificity of initial symptoms, diagnosis may be postponed until advanced stage. Therefore, it is critical that rapid and reliable diagnostic techniques be developed for brain tumors.

Imaging of the brain via magnetic resonance imaging (MRI) has changed the way we view and evaluate the brain. MRI is regarded as the best method of detecting brain tumors because of its many features; for example, MRI has superior contrast resolution, meaning it MRI is also safe to use because it doesn't use any type of ionizing radiation for imaging; CT is an example of a method that uses ionizing radiation.

Another feature that sets MRI apart from CT is that MRI is able to image the brain from three different angles (axial, sagittal, and coronal) creating an image of the tumor in three-dimensional space. MRI uses several imaging sequences to evaluate the brain, with the most commonly used being T1- weighted, T2- weighted and FLAIR images. Each of these sequences provides the clinician with important information related to the tumor's size, how much swelling is present, and the tissue type of the tumor. MRI can be repeated many times without causing harm to the patient, allowing for continued monitoring of a patient's tumor or disease and their response to treatment.

The combination of the large number of medical imaging scans collected and the advancements in technology over the past twenty years have helped to develop artificial intelligence as a new way of diagnosing patients. Machine learning (especially deep learning) can accurately identify, extract pertinent features, and classify different types of tumors and diseases with great accuracy; in some years machine learning can do as well or better than human experts in performing the same tasks.

Convolutional neural networks (CNNs) represent a special application of deep learning that enables the computer to process images using various levels of abstraction, without the need for humans to label previously identified patterns enhancement will vary depending on the level of necrosis and grade of the tumor. Thus, gliomas pose considerable characteristics and clinical challenges, relating to being the most tumor, and the surrounding tissue when compared to CT. Compared to conventional techniques, there are numerous advantages of using CNN's for the detection of tumors in the human brain.

I. Literature Review

Classifying Brain Tumors and Their Etiology and Clinical Relevance

Brain tumors are a diverse category of many different types of neoplasms that exhibit varying biological performance, treatment response & prognostic outcomes. The three most common types of primary brain tumors studied using machine learning are gliomas, meningiomas and pituitary adenomas; all three differ in their radiological aggressiveness. Gliomas originate from the glial cells, providing a metabolic and structural support to neurons, and form the basis of classification based upon histopathological characteristics as Grade 1-4 by the World Health Organization.

Glioblastoma multiforme is a Grade 4 malignant form with the poorest prognosis due to its aggressive growth pattern and the least effective treatments, exhibiting a median survival of approximately 12-15 months despite aggressive therapy. Gliomas have infiltrative patterns of growth, making total surgical resection either impossible or impractical; therefore, they require multimodal treatment approaches.

Radiologically, gliomas appear as relatively heterogeneous masses with irregular borders and surrounded by oedema, and the nature and pattern of enhancement will vary depending on the level of nicrosis and grade of the tumor.

Meningiomas develop from arachnoid cap cells located in the membranes that surround and protect the brain and spinal cord. They account for roughly 30% of primary brain tumors. Most meningiomas are classified as WHO Grade l, which are characterized by well-defined boundaries. Meningiomas typically have classic MRI findings including exeso-axially located, homogeneous contrast enhancement, and the "dural tail" sign which represents the thickened dura of the surrounding area.

Atypical (Grade II) and anaplastic (Grade III) meningiomas tend to grow more aggressively and are more likely to recur, often requiring more intensive treatment strategies. In contrast, WHO Grade I meningiomas are usually less aggressive and generally have a favourable prognosis, particularly when they are completely removed through surgery.

Pituitary adenomas originate in the anterior pituitary gland and are considered the third most common type of intracranial tumor.Pituitary adenomas can be functionally active (i.e., they secrete hormones) or non-functionally active (e.g., they do not secrete hormones). The clinical aspects of estas adenomas by determining the causes of endocrinopathies such as hyperprolactinemia, acromegalia, and Cushing's disease. Non-functionally active adenomas may cause mass effects (e.g., increasing pressure on the optic chiasm and causing visual field defects) and headaches.

MRI characteristics of pituitary adenomas include sellar/ suprasellar location, homogeneous MRI intensity, and variable patterns of contrast enhancement. Accurate classification of mitotsis of andenomas is essential determining what is and is not appropriate for surgical, medical, radiation theory.

Deep learning has changed how machines are used to analyze the contents of images by providing the capability to automatically learn multiple hierarchical features directly from raw pixel data. Convolutional neural networks have been the leading architecture type for visual-based applications due to their ability to learn translation-invariant features- as demonstrated in the CNN architecture that has been modeled after the hierarchical layout of the human visual cortex and the methodology

used to perform convolutional operations on images. Finally, ResNet- 50's feature extraction capabilities differentiate between the subtle characteristics that differentiate glioma, meningioma, and pituitary adenomas in ways that lead to accurate identification.

Deep Learning Models for Identifying Cerebral Tumors

ResNets (Residual Networks) are the first neural network architecture to use residual connectionsa technique developed to overcome the vanishing gradient issue commonly encountered in very deep neural networks. ResNet employs skip- connections that create an uninterrupted gradient path from the output of the network back to the input during the process known as back-propagation. This feature has enabled the successful training of 50, 101, or even 152 layer neural networks. ResNet-50 is a neural network that has 50 layers arranged in an organizational model (Block) called residual blocks, and has demonstrated outstanding results when classifying brain tumor types.

ResNet-50's lateral skips connections allow for gradient flow through the network. For example, in experimental studies, ResNet-50 demonstrated a 96.50% accuracy for the detection of brain tumors, compared to 93.45% for GoogleNet, 89.33% for VGGNet, while requiring less computation time. This effectiveness of the ResNet-50 architecture results from the network's ability to learn identity mapping, which provides a performance boost when additional layers are unnecessary, and mitigates the likelihood of deteriorating performance in deeper networks. Furthermore, ResNet-50 testing accuracy has been reported to be 97.91% with an F1-score of 97.95% for identifying and classifying four types of brain tumors, making it one of the best architectures for brain tumor classification.

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II. Methodology

Dataset Acquisition and Description

The dataset for this study contains 7,023 high- resolution MRI (Magnetic Resonance Imaging) brain tumor images, which were collected from multiple sources, and were sorted into four diagnostic categories: 1,621 glioma images, 1,645 meningioma images, 1,757 pituitary tumor images, and 2,000 normal (no tumor) brain images. The dataset was designed to allow the use of multi-class supervised learning techniques for performing tumor type classification and/or tumor presence/absence classification.

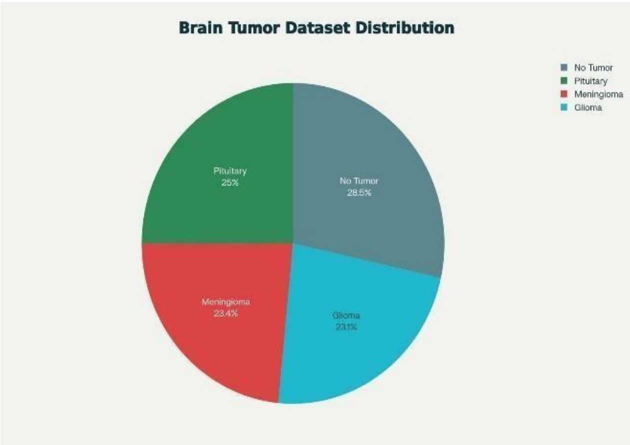

Fig. 1 Distribution of Brain Tumor MRI Data set across four categories.

The dataset also provides a reliable and standardized method for acquiring and using brain MRI data through public repositories, including the CE-MRI (Contrast-Enhanced MRI) Figshare dataset, which includes clinically validated standardized brain MRI scans with radiologist expert annotations.

The dataset has good class balance and presents an important feature for minimizing bias in the development of models due to the majority class (i.e., normal brain images) when training the models.

Since the dataset contains more normal brain images (2000) than tumor images (1621–1757), an imbalance exists between the two classes, the data set will provide a practical presentation of how the majority of patients would be recommended to undergo brain MRI screening when the number of healthy patients to people with a tumor are essentially the same. The T1-weighted MRI images in the dataset were obtained using standard clinical MRI protocols and were acquired using a series of contrast-enhanced T1- weighted MRI sequences that provide optimal visualization of tumors this occurs because of the breakdown of the blood–brain barrier, which leads to enhanced contrast in tumor regions. Additionally, the images in the original dataset had different dimensions, making it necessary to standardize their sizes before processing so they could be used effectively as input for a Convolutional Neural Network (CNN).

The dataset was divided using stratified random sampling to preserve the class distribution in each subset. Typically, around 70-80% of the images were allocated for training, while the remaining 20-30% were used for validation.

This partitioning method guarantees that the models used to assess generalization performance will be based on previously unseen datasets, providing unbiased estimates of performance in real world clinical environment.

System Architecture and Computational Workflow

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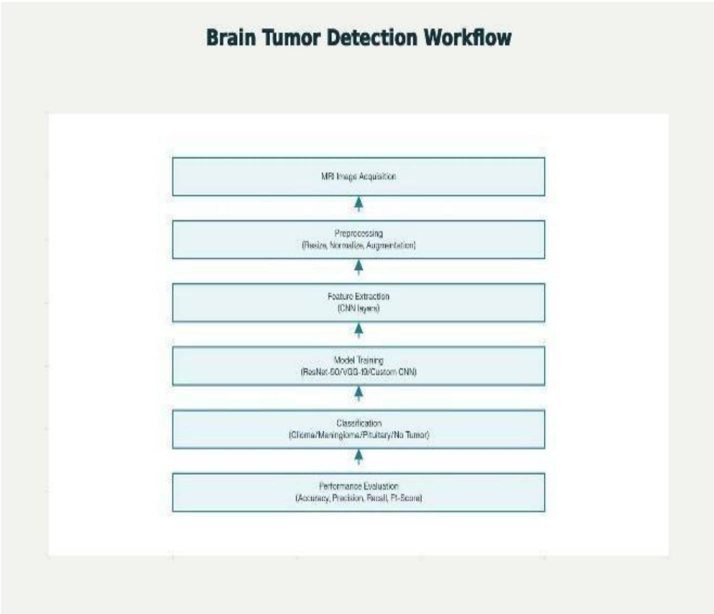

Fig. 2 Flow Chart of Brain

Tumor Detection Methodology using ML.

The pipeline for acquiring brain tumors consists of six steps:

(1) obtaining a brain MRI, (2) preprocessing the raw MRI images prior to feature extraction, (3), extracting features from the MRI images, (4), training a predictive model from the extracted features, (5), classifying the brain MRI images, and (6), evaluating the predictive accuracy of the classification system.

The modular nature of the system will enable the systematic optimization of component systems with an emphasis on maintaining the functionality of the overall system.

Step 1 - in acquiring a brain MRI is to obtain a brain MRI from a clinical MRI scanner using standardized protocols to provide consistent image quality (i.e., resolution, contrast, and acquisition protocol). T1-weighted sequences with gadolinium contrast enhancement provide the best visualization of tumors.

Step 2 - in pre-processing the raw MRI images involves a series of transformations including resizing, normalization, and reducing noise to prepare the data for use in processing by a neural network.

Step 3 - Feature extraction from MRI images is performed using a Convolutional Neural Network (CNN), which automatically learns hierarchical feature representations. It starts by identifying low-level features such as edges and textures and gradually progresses

to higher level features that distinguish between different tumor types.

Step 4 - is to train CNN architectures (e.g. ResNet-50, VGG-19) using back- propagation and gradient descent optimization to minimize the classification loss functions on each of the trained models.

Step 5 - is to classify the MRI images using the trained models to produce a probability distribution across 4 classes then fully connected layers for classification.

Step 6 - The performance evaluation of the model consists of making predictions with the model and then comparing the predictions to the ground-truth labels to determine accuracy, precision, recall, F1-score and confusion matrices for the

Architecture Types of the Model:

Three (3) different types of deep learning architectures were built and compared:

ResNet-50 - A 50 layer residual network using skip connections to allow gradients to flow through deep network layers. The architecture has successive convolution layers that use Batch Normalization and ReLU activations, followed by global average pooling and (99.06%), precision (98.73%), recall

(99.13%), and F1-score (98.79%) results that are at or near optimum classification results. In addition, a hybrid GAN + are at or near optimum classification results. In addition, a hybrid GAN + Swin transformer model has achieved exceptional test accuracy rates on the Figshare and Kaggle datasets (99.54% & 98.9% respectively).

Custom CNN - A compact deep learning model with fewer layers, created to improve computational efficiency. It typically includes convolutional layers, pooling layers, dropout for regularization, and fully connected (dense) layers.

Result

Comparative Evaluation of Model Performance

Various CNN architectures show different levels of performance when tested against an experimental brain tumor classification. For brain tumor classification, ResNet-50 is determined to have the highest performance based on test accuracy (97.91%) and F1-score (97.95%); thus it is the best multilabel brain tumor classification model. VGG-19 has a test accuracy of 95.83% and F1-score of 96.0%, thus outperforming a significant degree (approximately 2%) compared with ResNet-

50. Whilst cutting edge, with regards to transfer learning and fine-tuning approaches, state-of-the-art models have produced substantially better results than previously reported.

YOLOv11 has achieved the highest test accuracy (99.56%) of any object detection model to-date, while YOLOv8 has achieved an excellent accuracy rate of 99.49%. Furthermore, using EfficientNetB2 models as a base, a recent study reported test accuracy (99.06%), precision (98.73%), recall

(99.13%), and F1-score (98.79%) results that are at or near optimum classification results. In addition, a hybrid GAN + Swin transformer model has achieved exceptional test accuracy rates on the Figshare and Kaggle datasets (99.54% & 98.9% respectively).

Results of the comparison show that the residual learning architecture using ResNet- 50 gives great benefits as a result of having residual connections to help with better gradient flow and feature learning versus sequential architectures like VGG-19. Additionally, both models showed an increase in the processing speed for ResNet-50 over VGGNet by 10%, while still achieving a higher level of accuracy in the end result making it a better choice for clinical

application where accuracy and processing efficiency would both be important.

III. Conclusion

All research findings confirm that automated detection methods using Deep Learning techniques and specifically advanced CNN (e.g., ResNet 50), are both effective and provide a high level of accuracy and reliability when detecting brain tumours from MRI images. Residual connections associated with ResNet-50 allow for the effective propagation of gradients through deep networks promoting improved feature learning compared to both VGG-19 and custom CNNs result in ResNet-50 delivering superior performance (97.91% accuracy). Class-specific performance showed the majority of tumour categories were well represented and identified with gliomas (100% accuracy) and pituitary tumours identified with (99.33% sensitivity) demonstrating particularly strong performance. These results indicate that CNN-based systems can be vital decision-support systems for radiation oncologists, thus reducing decision time frame and minimising human error in the knowledge-based interpretation of MRI images.

Future areas of study will consist of integrating attention mechanisms to better locate features, further understanding the benefits of using ensembles of models with different architectures, expanding model performance analytics to 3D-analysis of MRI volume, and developing studies to support the use of AI-based diagnostic methods in practice.

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