Brain Tumor Detection using Image Segmentation through Neural Network

ʼishavjeet Singh
Computer Science and Engineering
Amity School of Engineering and Technology
Noida, India

Ansit Guta
Computer Science and Engineering
Amity School of Engineering and Technology
Noida, India

Priyansh Chauhan
Computer Science and Engineering
Amity School of Engineering and Technology
Noida, India

Dr.Ram Paul
Assistant Professor
Computer Science and Engineering
Amity School of Engineering and Technology
Noida, India

***Abstract*— Diagnosing a brain tumor takes a long time and relies heavily on the radiologist's abilities and experience. The amount of data that must be handled has increased dramatically as the number of patients has increased, making old procedures both costly and ineffective. Many researchers investigated a variety of algorithms for detecting and classifying brain tumors that were both accurate and fast. Deep Learning (DL) approaches have recently been popular in developing automated systems capable of accurately diagnosing or segmenting brain tumors in less time. DL enables a pre-trained Convolutional Neural Network (CNN) model for medical images, specifically for classifying brain cancers. Medical images can be classified into four different categories : Pre-Processing, Segmentation, Optimization and Feature Extraction. The proposed model is to use a deep Convolutional neural network with VGG-19. All CNN models are analyzed using performance measures such as precision, accuracy, specificity, and recall.**

Keywords- Convolution Neural network, Image detection, Python , Deep learning.

I. INTRODUCTION

1.1 Objectives:

The primary objective of this research paper is to explore and analyze the implementation of convolutional neural network(CNN) in the context of Brain tumor detection while adhering to the highest standards of academic integrity and originality. In pursuit of this objective, our aim is to investigate the feasibility, efficacy, and implications of integrating CNN model to detect brain tumor through MRI, with a particular emphasis on ensuring that all content presented is original and free from plagiarism.

1.2 Significance of Brain Tumor detection using Image processing :

The Neural Network is crucial for the safe and efficient operation of Brain Tumor detection. By accurately identifying and segmenting the brain through MRI, this model can make informed decisions, reduce human error, and simplify the process. Successful Image processing algorithms are essential for fulfilling the promise of safer and more reliable models to detect brain tumors.

1.3 Background:

Brain Tumor detection using machine learning have already seen lot of literature and experimental work, and the more successful work was on neural network. Neural network are the combination of layers through which we provide information and detect at every layer. .[1] VGG-19 has shown promising result in different fields so we expect in brain tumor detection it will be ore reliable and accurate model [2]. VGG-19 allows the transfer of learning .[3] This report focuses on developing models and the challenges.

II. SCOPE

2.1 Exploration of Neural Network:

Our first objective is to comprehensively explore the underlying principles, methodologies, and advancements in VGG. By conducting an in-depth review of relevant literature, academic papers, and industry developments, we seek to gain a thorough understanding of the theoretical foundations and practical applications of VGG architecture.

2.2 Analysis of Neural Network:

Building upon the foundational knowledge acquired through literature review, our next objective is to analyze the specific challenges, opportunities, and implications of integrating Brain Tumor detection into system. This analysis will encompass factors such as segmentation of MRI images, segmentation techniques, and regulatory considerations, with a focus on identifying key insights and potential areas for further research.

2.3 Development of Original Insights and Findings:

VGG-19, a pre-trained convolutional neural network (CNN), has emerged as a powerful tool for brain tumor detection in MRI scans..VGG-19 pre-trained on massive image datasets can be fine-tuned for brain tumor classification. Analyzing the learned filters in the initial layers post fine-tuning might reveal novel image features crucial for brain tumor identification.Techniques like LIME (Local Interpretable Model-agnostic Explanations) can be used to understand why VGG-19 classifies an image as cancerous or benign.

2.4 Convolution Neural network:

2.4.1 VGG-16 Neural Network :

VGG-16 is a convolutional neural network model designed for image classification tasks.The VGG-16 configuration typically consists of 16 layers, including 13 convolutional layers and 3 fully connected layers organized into blocks with multiple convolutional layers followed by max-pooling layers for downsampling. The input dimensions are (224, 224, 3), and the architecture includes various convolutional layers with different filter sizes, max-pooling layers, and fully connected layers corresponding.VGG-16 has limitations such as being slow to train and requiring substantial computational resources due to its large number of parameters

2.4.2 Selecting and Utilizing Relevant Python Libraries:

TensorFlow, OpenCV, PyTorch: These popular libraries offer comprehensive toolsets for various deep learning tasks, including object detection. They provide functionalities for image and video preprocessing, model building, training, and inference.

Scikit-image: This library offers utilities for image processing, manipulation, and feature extraction, which can be beneficial for preparing data for CNN models.

Keras (with TensorFlow): This high-level API simplifies deep learning model building within the TensorFlow framework, making it easier to design and experiment with neural network architectures for CNN

2.4.3 Developing Algorithms for Image segmentation and Detection:

VGG-19 comes pre-trained on a massive image dataset. This pre-trained knowledge can be leveraged as a starting point for brain tumor classification. By fine-tuning the final layers of VGG-19 with labeled brain tumor MRI scans, the model can adapt to the specific task of identifying tumors.

CNN (Regions with CNN features): This family of models (e.g., Fast R-CNN, Mask R-CNN) uses selective search to propose regions and then employs CNNs for object classification and segmentation the MRI.

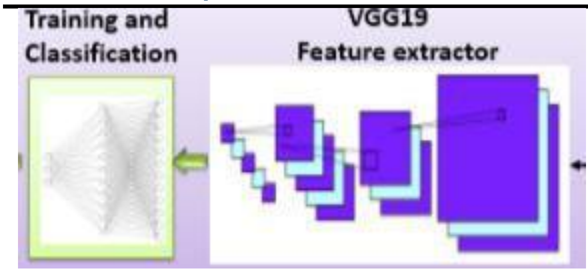


Figure 1: VGG-19 model

Feature Extraction and Classification: The initial layers of VGG-19 act as powerful feature extractors. During fine-tuning, these layers learn to identify relevant features in brain MRI scans, such as textural patterns or intensity variations, that might be indicative of tumors.

The final layers, added during fine-tuning, take these learned features and classify the image as containing a tumor or not (binary classification) or categorize the tumor type (multi-class classification).

Figure 2: VGG-19 architecture

2.4.4 Implementing Deep Learning Models:

Convolutional Neural Networks (CNNs): These are the backbone architectures for most modern object detection models. They are designed to extract features from images through convolutional layers, allowing them to learn patterns and representations relevant for object identification.

Transfer Learning: Pre-trained models like VGG19, ResNet50, or InceptionV3 can be utilized as feature extractors. Their weights learned on large datasets like ImageNet can be fine-tuned for specific Image detection tasks, reducing training time and improving performance.

Data Augmentation: Artificially expanding the training data through techniques like random cropping, flipping, or color jittering can improve model robustness and generalization to unseen variations in dataset.

2.4.5 Evaluation and Refinement:

Metrics: A number of recent studies used confusion matrices to analyze models and assess the level of performance of the classification process, categorizing relationships between data and distributions. By using different confusion matrices, classification models may be assessed extensively.

2.4.6 Considerations for Project Scope:

Real-time vs. Offline processing: Detecting the brain tumor in Real-time MRI scanning and making detection in the early stage possible.

Hardware constraints: Consider the hardware resources (CPU, GPU, memory) available for running the Image processing, as these can influence the choice of libraries, models, and algorithms.

Data availability: Ensure access to a well-annotated dataset containing labeled images or videos relevant to the target objects for training and evaluating the developed models.

2.4.6 Environment Setup:

A key aspect of the project involves configuring the development environment. This encompasses the installation and setup of the necessary model, frameworks, and libraries required for the development and testing of CNN (VGG-19).

Required a large set of data of different brain scans while keeping ethical consideration.

2.4.7 Data Collection:

To train and validate the object detection system, the project will include the collection and preprocessing of relevant datasets. The scope involves sourcing and annotating datasets containing images of various brain anatomy, brain tumor including different types of MRI such as normal, glioma, , meningioma, metastatic and pituitary.

We also have to keep ethical considerations in mind while keeping data of our users as private, we could directly train model with the data without saving it in the system.

2.4.8 Model Selection and Training:

The project encompass the selection of suitable deep learning models, such as Convolutional Neural Networks (CNNs), for object detection. This includes the training of these models using the annotated datasets to ensure the model ability to accurately recognize MRI.

Table 1. *Architecture details of the VGG19+CNN model. The max pooling layer is applied after each convolution layer.*

'GG19 + CNN Model	*)utput Shapes*
Conv (3X3)_64]X22	*24X224X64*
Conv (3X3)_128]X2	*12X112X128*
Conv (3X3)_256]X4	*6X56X256*
Conv (3X3)_512]X4	*8X28X512*
Conv (3X3)_512]X4	*4X14X512*
1ax pool	*X7X512*
'latten	*5,088*
)ense (relu)	*096*
)ropout (0.5)	*096*
)ense (relu)	*096*
)ropout (0.5)	*000*
)ense (SoftMax)	

2.4.9 Processing of data:

Pre-process your MRI dataset using image processing techniques. Implement your chosen data augmentation techniques during training. This can be done within your training loop using libraries like imgaug.

Train the VGG-19 model with the augmented data. The model will learn to identify tumor features regardless of variations like slight rotations or brightness changes.

2.4.10 Performance Metrics:

The project involve the definition and measurement of performance metrics to assess the effectiveness of the Image detection system. Metrics may include accuracy, precision, recall, and latency, among others.

four primary keys—a true positive (Tp), a true negative (Tn), a false positive (Fp), and a false negative value (Fn)

$$\textbf{Accuracy}\ (\text{ACC}) = \frac{Tp + Tn}{Tp + Tn + Fp + Fn}$$

$$\textbf{Specificity} = \frac{Tn}{Tn + Fp}$$

2.4.11 Challenges and Solutions:

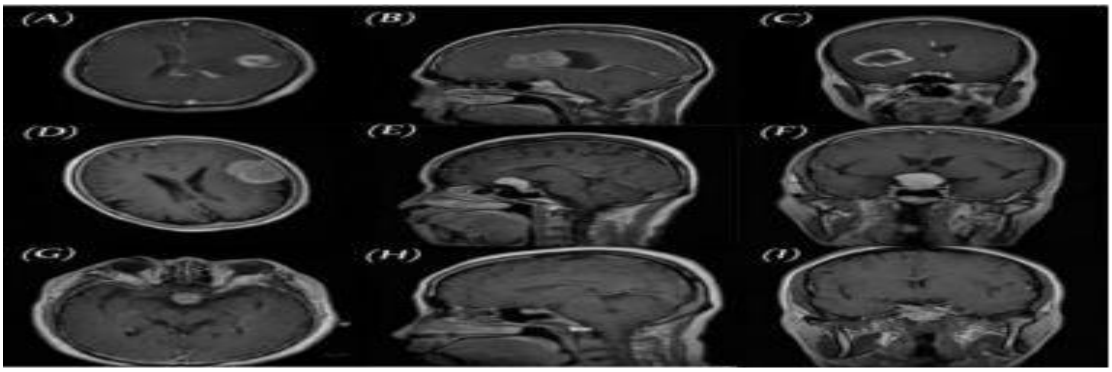
While the primary focus is on software development, the project will also address challenges encountered during the development process. These challenges may include data annotation, model optimization, and achieving processing capabilities. The scope encompasses the exploration of solutions to overcome these challenges.

Fine-tuning Hyperparameters: Tuning learning rate, epochs, etc., is crucial for optimal performance. Class Imbalance: Datasets might have fewer tumor cases. Techniques like oversampling or weighted loss functions can help. Interpretability: Understanding VGG-19's decision-making process can be challenging. Techniques like CAMs can offer insights.

2.4.12 Regulatory and Ethical Considerations

Data Privacy and Security: ML models require large datasets of medical images and patient information. Stringent data privacy regulations like HIPAA (US) or GDPR (EU) need to be followed to protect patient privacy and data security. Measures like anonymization and secure storage practices are essential..

ML algorithms can inherit biases from the data they are trained on. This could lead to false positives or negatives for certain demographics. Rigorous data curation and bias mitigation techniques are crucial to ensure fair and equitable outcomes for all patients.



igure 3: *Different types of MR images for dataset*

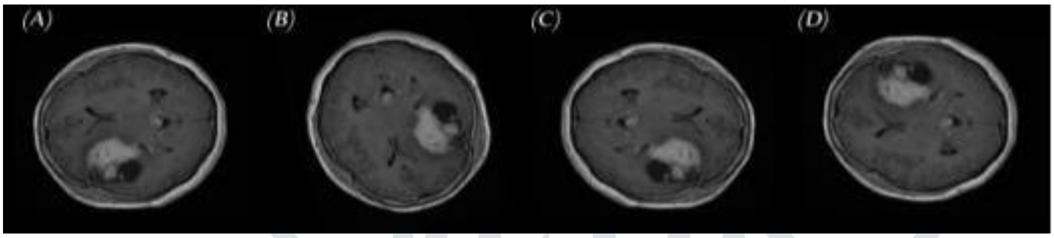


Figure 4: Samples of brain tumor MRIs and results of augmentation: (A) primary MRI, (B) rotation, (C) left-right mirroring, and (D) up–down flipping

III. LITERATURE REVIEW

3.1 Deep Learning with Pre-trained Models Shows Promise:

Convolutional Neural Networks (CNNs) have achieved remarkable success in brain tumor detection. VGG-19, a pre-trained CNN, demonstrates significant potential due to transfer learning. Its pre-trained weights, learned from a massive image dataset, provide a strong foundation for feature extraction in brain MRI scans. Researchers can then fine-tune the final layers to focus on identifying tumor-specific features. Studies report high accuracy in brain tumor classification using VGG-19, highlighting its effectiveness.

3.2 Image Processing Techniques Enhance Feature Extraction:

Traditional image processing techniques play a crucial role in conjunction with deep learning models. Segmentation methods like k-means clustering or region growing algorithms separate MRI scans into distinct anatomical regions. This allows for focused analysis on areas more likely to harbor tumors. Additionally, feature extraction techniques can quantify characteristics like pixel intensity, texture, and shape within these regions. These features, combined with deep learning models, provide a rich set of information for robust tumor classification.

3.3 Existing Object Detection Approaches

Several detection approaches have been proposed for Brain Tumor detection, The machine learning competition platform Kaggle has numerous kernels showcasing brain tumor detection using VGG-19. These kernels often include pre-trained models or code for fine-tuning VGG-19 on brain tumor datasets

IV. CONSTRAINTS

4.1 Data Availability: Limited Training Data:

Medical datasets, particularly for rare tumors, can be limited. This can lead to overfitting if not addressed with techniques like data augmentation. Data Privacy and Security: Strict regulations surround patient data privacy. De-identification and secure storage practices are essential.

4.2 Computational Resources:

Hardware Requirements: Training deep learning models, especially VGG-19, requires powerful GPUs with sufficient memory. This can be a barrier for resource-constrained settings. Training Time: Training VGG-19 from scratch can be time-consuming. Leveraging pre-trained weights and optimizing training parameters can mitigate this.

4.3 Model Interpretability:

Black Box Nature: Deep learning models can be complex and difficult to interpret. Understanding why the model makes specific classifications can be challenging. Explainability for Clinical Use: For clinical adoption, healthcare professionals require some level of understanding of the model's decision-making process.

4.4 Generalizability and Bias: Dataset Bias:

Biases present in the training data can be inherited by the model, leading to inaccurate predictions for certain demographics.

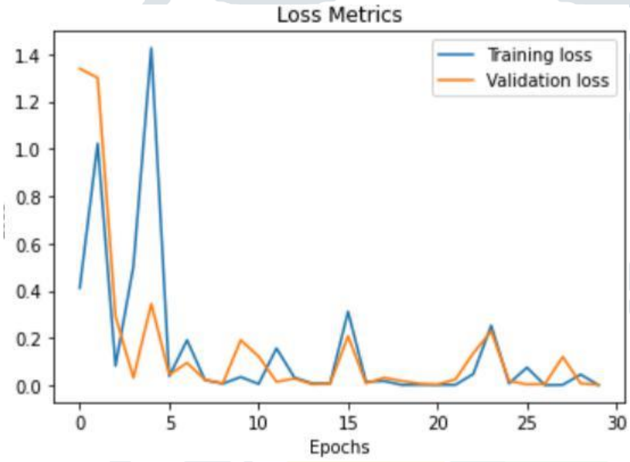
4.5 Generalizability to New Data:

Models trained on specific datasets might not perform well on unseen data with different characteristics. Techniques like data augmentation can help improve generalizability. Ethical 4.6 **Considerations:** Informed Consent: Patients should be informed about the role of AI in their diagnosis and have the right to choose whether or not to participate.

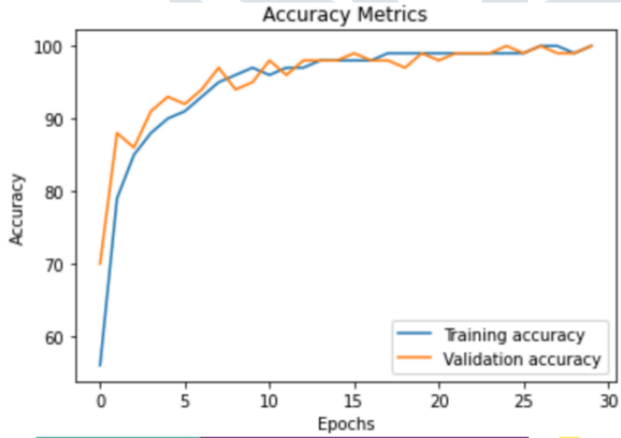
4.7 Accountability:

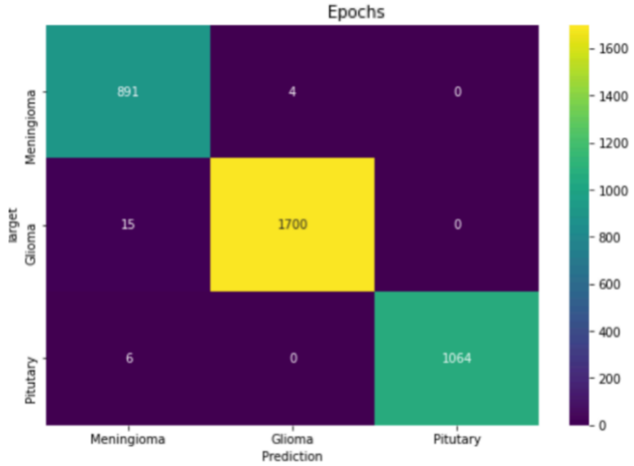
Clear guidelines are needed regarding accountability in case of misdiagnosis or errors arising from the model.

V. RESULT AND ANALYSIS



The graph suggests that the model is well-trained and able to accurately predict the presence or absence of a brain tumor in the validation dataset. The smooth and steady decrease in both the training and validation loss indicates that the model is not overfitting to the training data and is able to generalize well to new, unseen data.





●Precision (positive predictive value) for pituitary tumors:
1.67%
- Precision for glioma tumors: 94.12%
- Precision for meningioma tumors: 0.57% ● Recall (sensitivity) for pituitary tumors: 0% ● Recall for glioma tumors: 93.75%
- Recall for meningioma tumors: 0.57%
- F1 score for pituitary tumors: 0.33%
- F1 score for glioma tumors: 93.93%
- F1 score for meningioma tumors: 0.11%

VI. CONCLUSION

In conclusion, The recent research work in tumor classification based on MR images has witnessed some challenges, such as the number of images in the data set, and the low accuracy of the designed models. This work proposed a complete framework based on a deep learning model as feature extractors with different classifier models designed to classify MRIs of gliomas, meningiomas, and pituitary tumors using different types of augmentations. The feature extractor VGG19 was used to extract features of brain tumor MRIs. Three types of classifiers were then tested

Our study tested the classification of only three general brain tumor types: meningiomas, gliomas, and pituitary tumors. This constitutes a limitation of the study since other types of brain tumors exist. Moreover, our synthetic images were 256 × 256, while the primary data set images were all 512 × 512. Because of limitations of computational resources, the input for the model was resized to 224 × 224. In future studies, we aim to work on acquiring primary images with appropriate size in order to make the images as realistic as possible to a radiologist.Looking forward, VGG-19 serves as a stepping stone for further advancements. Exploring ensemble learning with other architectures and integrating VGG-19 with other modalities hold promise for even better performance.

ENCES

[1] American Brain Tumor Association. (2010). *Facts and statistics, 2010. Retrieved*

[2] Central Brain Tumor Registry of the United States (2010). *CBTRUS statistical report:Primary brain and central nervous system tumors diagnosed in the United States in 2004–2006.*

[3] Sidney Croul, Jessica Otte and Kamel Khalili, "*Brain tumors and polyomaviruses", Journal of NeuroVirology, 9: 173–182, 2003*

[4] S. M. Bhandarkar and P. Nammalwar, "*Segmentation of Multispectral MR images Using Hierarchical Self-Organizing Map," Proceedings of Computer-Based medical system CBMS 2001.*

[5] C. A. Parra, K. Iftekharuddin and R. Kozma, *"Automated Brain Tumor segmentation and pattern Recoginition using ANN," Computional Intelligence Robotics and Autonomous Systems, 2003.*

[6] Andreas Rimner, Andrei I. Holodny and Fred H. Hochberg, *"Perfusion Magnetic Resonance Imaging to Assess Brain Tumor Responses to New Therapies," US neurological disease, 2006.*

[7] V. J. Nagalkar and S. S. Asole, *"Brain tumor detection using digital image processing based on soft computing," Journal of Signal and Image Processing , Vol. 3,No. 3, pp.-102-105, 2012*

[8] J. Alirezaie, M. E. Jernigan and C. Nahmias, "*Neural Network based segmentation of Magnetic*

Resonance Images of the Brain," IEEE

[9] R. Hodgson, D. Bailey, M. Naylor, A. Ng, and S. McCNeil, *"Properties, Implementations and Applications of Rank filters", Image Vision Comput., 3, pp. 3–14, 1985.*

[10] M. Cree, *"Observations on Adaptive Vector Filters for Noise Reduction in Color Images",*

IEEE Signal Processing Letters, 11, No. 2, pp. 140–143, 2004.

[11] P. Lambert and L. Macaire, *"Filtering and Segmentation: The Specificity of Color Images", Proc. Conference on Color in Graphics and Image Processing, Saint-Etienne.*

[12] I. Pitas and P. Tsakalides, *"Multivariate Ordering in Color Image Filtering", IEEE Transactions on Circuits and Systems for Video Technology, 1, pp. 247–259, 1991.*

[13] R. Lukac, B. Smolka, K. Plataniotis, and A. Venetsanopoulos, "*Selection Weighted Vector Directionnal Filters", Computer Vision and Image Understanding, 94, pp. 140–167, 2004.*

[14] M. Vardavoulia, I. Andreadis, and P. Tsalides, *"A New Median Filter for Colour Image Processing", Pattern Recognition Letters, 22, pp. 675–689, 2001.*

[15]*https://github.com/aksh-ai/neuralBlack/blob/master/torch_brain_tumor_c lassifier.ipynb*