Brain tumor detection using Region-based Convolutional Neural Network and PSO

G. Laxmi Deepthi[1], D. Shyam Kumar[2], G. Soumith[3], SK. Yasmin Sulthana[4], S. Arun[5]

[1]Assistant Professor, Dept. of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[2,3,4,5]Student, Dept. of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India

---***---

Abstract - *The most prevalent and deadly disease, brain tumors, have an extremely low life expectancy. This study uses deep learning algorithms to categorize and identify human brain tumors Which we are using to train the dataset for deep neural networks. Since new data cannot be trained, the accuracy level of the current analysis is insufficient. Here, the brain tumor is detected using the Region Convolutional Neural Network (R-CNN) VGG16 model and the DensNet model and segmented from the MRI images using Particle Swarm Optimization (PSO) (normal, benign, malignant). The dataset has undergone extensive feature analysis and segmentation training. We achieve the highest accuracy by combining PSO with R-CNN.*

***Key Words*: VGG16, DenseNet, RCNN, PSO**

1. INTRODUCTION

Brain tumors are essentially the uncontrolled expansion of malignant the cells in the brain, as opposed to a tumor, essentially the unchecked expansion of malignant cells in any region of the body. Different types of brain tumors exist. The word "benevolent" refers to a group of aberrant, non-cancerous brain cells. Adenomas and fibroids are two examples of benign tumors. Pre-malignant brain tissue is a group of aberrant cells that are not cancerous but have the capacity to develop into malignant cells. The most severe sort of tumor is malignant, which is a collection of diseased cells. Sarcoma and carcinoma are two examples of malignant tumors. A person's life can be saved if a brain tumor is found and treated properly.

In India, the frequency of brain tumors is gradually increasing, and more instances are reported each year among people of all ages. According to reports, brain tumors are India's tenth most prevalent cancer form. The International Association of Cancer Registries claims that (IARC), India reports about 28000 cases of brain cancer each year, and sadly, Brain tumours cause 24000 deaths annually. Brain tumours are a dangerous medical condition. If found and treated improperly, can be fatal. In a single year, over 330,000 children and adults received diagnoses of CNS cancer worldwide, and this figure is continuing to climb along with the rising mortality rate of brain tumors. CNS cancer accounts for 2% of all cancers in India, and the incidence ranges from 5 to 10 per 100,000 people, with an increasing trend. A person's chance of surviving for five years is 36%, while their chance of surviving for ten years is 31%.

A patient's life expectancy can be extended by a timely diagnosis of a brain tumor. Typically, imaging data analysis of brain tumor pictures is used to make the diagnosis of brain tumors. In order to accurately assess brain tumor photos, there are several important steps that must be taken. Non-invasive imaging technique magnetic resonance imaging (MRI) generates intricate, three-dimensional anatomical images. It is frequently used for disease detection, diagnosis and therapeutic monitoring image. Consequently, the various imagining auxiliary circumstances, there are four different types of brain MRI imaging modes: weighted T1 mode, Flair mode, T1 ce mode, and T2 weighted mode. Different modes can show various aspects of a brain tumor. The classification and it is possible to identify brain tumors accomplished using a variety of techniques, most notably CNN models EfficientNet B0, Inception V3, Xception, Gaussian Convolutional Neural Network, and Fuzzy C Means Clustering.

The BRATS2019 dataset, which covers the four modes of MRI images, is being used in this research as part of a method as the detection of brain cancer. Images of brain cancers were used strategies for processing medical images, such as pre-processing and the optimization technique, were utilized to segment the medical image images. The data was then trained with two CNN models, which assisted in classifying brain tumors and identifying their various forms. Enhancement, filter operation, segmentation, and feature extraction are all included in the pre-processing, while feature identification and extraction are included in the post-processing.

2. RELATED WORK

[1] Hasnain ali shah, Faisal Saeed, (2022) this paper done by utilizing a model within a convolutional neural network, **"A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet"** named

EfficientNet B0, we have identified a brain tumor in the magnetic resonance scans. They have employed methods for processing images transform poor-quality photos into high-quality ones. Image segmentation is accomplished using dilation and erosion techniques. The EfficientNet B0 model is trained on a dataset of 3000 MR images to identify brain tumors. The validation accuracy of the suggested method was 98.87%. The accuracy of this model is compared in this study to that of the VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 models. Less data was trained, and the t One would divide the three glioma grades into grades two, three, and four; the other would classify tumors into meningioma, pituitary, and glioma. These datasets include 233 and 73. In this paper type of tumor was not identified.

[2] Mohammad Rizwan, Aysha Shabbir, (2022) in their paper titled "**Brain Tumor and Glioma Grade Classification using Gaussian Convolutional Neural Network**" devised a method to employ a gaussian brain cancer classification using convolutional neural networks. In this investigation, three different datasets were used: one to One would divide the three glioma grades into grades two, three, and four; the other would classify tumors into meningioma, pituitary, and glioma. These datasets contain 233 and 73 patients' T1-weighted MR scans, for a total of 3064 and 516 pictures, respectively. This method had accuracy rates of 99.8% and 97.14 percent. To identify the type of tumor and glioma grade, this system pre-processed the data using gaussian filters and trained the data using a gaussian convolutional neural network. Gaussian filters reduce noise and blur the image, but they don't improve the image's quality or accurately segment it.

[3] Syed Ali Nawaz, Dost Muhammad Khan, (2022) in their paper titled "**Brain Tumor classification Based on hybrid optimized multi feature analysis using magnetic resonance imaging dataset**" The study [1] [2] [3] y's goal is to use brain magnetic resonance imaging to construct a machine-vision-based classification model for brain tumors. For glioblastoma, meningioma, and metastatic brain tumor classification, see, a system known as a classification system for hybrid brain tumors (HBTC) developed. In this system, images are first pre-processed using K-S-L image enhancement to improve image quality. The pre-processed images are then segmented using threshold- and clustering-based segmentation. Following the extraction of features using the run length matrix and co-occurrence matrix, nine optimized features are chosen using the Fisher co-efficient technique. After selecting the optimized features, four different classifiers—Random Tree, Meta Bagging, Decision Tree, and Multilayer Perceptron—are used to classify the type of tumor. However, the machine learning algorithms used

[4] Ahmed S. Musallam, Ahmed S. Sharif, (2022) in their paper titled "**A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images**" A computationally light model with few Max pooling, convolutional, and training iterations was used in this study's architecture. This study suggests a three-step preprocessing method to improve image quality, along with a deep convolutional neural network. is used to accurately identify tumors of the pituitary, meningiomas, and gliomas. This report also illustrated how the proposed architecture and the current approaches were compared. This system's accuracy was 98.22% overall, 99% in glioma detection, 99.13% in meningioma detection, 97.3% in pituitary detection, and 97.14% in normal image detection. 3394 MR images were used in this work to train on and identify the various tumor types. With minimal training data and no specific techniques, image segmentation is performed.

[5] Nellum Norren, Sellapan Palnappan, (2020) in their paper titled "**A deep learning model based on concatenation approach for the diagnosis of brain tumor**" This model combines the two separate CNN models, Inception-v3 and DenseNet201, to detect brain tumors in MR images. First, the dataset is pre-trained using following the Inception-v3 model, the training and feature extraction are done using the DenseNet201 model. The accuracy provided by the suggested method is 99.34% and 99.51%, respectively. The type of tumor is not identified in this paper, and there is less trained data.

[6] Shariar Sazzad, Misba UI Hoque, (2019) in their paper titled "**Development of Automated Brain Tumor Identification Using MRI Images**" The strategy used in this study is using grayscale photos to detect brain tumors. Color in grayscale fluctuations are reduced before training the dataset, and noises are eliminated using a filter operation. The color segmentation in this method is dependent on thresholds. Due to our inability to adequately extract the features, there is no guarantee for segmentation. The results also include undesirable places.

[7] Sergio Pereira, Adriano Pinto, (2019) in their paper titled "**Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images**" The amount of data that an imaging technique like MRI produces limits clinical practice using exact quantitative evaluations, making it difficult to manually segment the images quickly. Due to the substantial spatial and anatomical variation among brain tumors, automatic segmentation is a difficult task; as a result, reliable and automatic segmentation methods are required. In this study, we investigate 33 tiny kernels as a part of a self-contained convolutional neural network segmentation technique. Given the fewer weights there are in the network, using small kernels enables the design of more intricate architectures and helps prevent overfitting. In addition, despite its rarity in pre-processing, we looked at the use of intensity normalization.

[8] Ming Li, Lishan Kuang, (2019) in their paper titled "**Brain tumor detection based on multimodal Information fusion and CNN** [5]" This strategy's primary goal is to increase the accuracy of its earlier strategies. Convolutional neural networks and multimodal information fusion are both used in this method. To improve accuracy and performance, they used a normalization layer between the pooling layer and the convolutional layer in this approach. In comparison to the two-dimensional detection network, the accuracy was much higher. First, this study converts multimodal 2D-CNNs to 3D-CNNs, allowing for the detection of brain lesions several modalities in three dimensions. The raw input of the 2D-CNN can be resolved., which calls for a wide neighborhood of defects, while also better extracting the modal of the informational differences. Tumor types are not identified, and improper image segmentation is used.

[9] Keerthi TK, Shoba Xavier (2018) in their paper titled "**An Intelligent System for Early Assessment and Classification of Brain Tumor"** The proposed system can be used for tumor type categorization and early diagnosis. There are four phases in the system. 1. image processing 2. segmentation thresholds for segmentation 3. GLCM can be used to extract characteristics from brain MRI data. SVM classification is the last step. With the GA-SVM classifier, the system will offer greater accuracy and expand its capacity for generating decisions. SVM is more productive and uses less memory. The device also determines the tumor's stage of growth and offers healthy suggestions. SVM only works well for smaller datasets; hence, it is not appropriate for larger datasets.

[10] Dr A Jagan (2017) in their paper titled "**A New Approach for Segmentation and Detection of Brain Tumor in 3D Brain MR Imaging**" This study uses Clustering using fuzzy C-means and the improved EM technique. The decision was taken during detection, and both approaches were processed and calculated based on which had a higher accuracy rate. The main goal of the method is to increase 3D Accuracy, sensitivity, and specificity brain MR images using fluid-attenuated inversion recovery-based segmentation. The fluid attenuation inversion recovery in the 3D brain MR image segmentation was the major focus of this investigation. Fuzzy c-means Euclidean distance measures give underlying factors unequal weight.

[11] Haocheng Shen and Jianguo Zhang (2017) in their paper titled "**Fully connected CRF with data-driven prior for multi-class brain tumor segmentation**" The automatic segmentation of brain tumors described in this study is based on FC-CRF. This paper's primary contributions are as follows: 1) Apply FC-CRF to segment brain tumors into multiple classes using a hierarchical approach. 2) compared grid CRF with FC, demonstrating that the latter greatly enhanced tumor border segmentation. Tumor boundaries that are segmented have greatly improved. They use a histogram for analysis. Processing time increases when the borders are widened and each image pixel is processed separately.

[12] R Lavanya Devi, Nivedita (2017) in their paper titled "**Classification and Segmentation of Brain Tumors in MRI Images using PNN**". The proposed process is broken down into four fundamental components. Preprocessing comes initially, followed by feature extraction using a gray-level cooccurrence matrix (GLCM). GLCM is the second matrix. Phase 3 is PNN-based categorization., followed by segmentation using the K-means clustering technique as the final step. Principal Component Analysis is used for picture recognition and compression (PCA). PNN has the best classification accuracy and is the fastest method. PCA successfully decreases the data's dimensionality. MRI imaging is more effective than CT scanning. First, a systematic review unearths a total of 18,725 potentially important scientific papers. Studies that focus on the actual observed behavior of app users rather than behavior reported via questionnaires have been found to have a research gap. This study looks at how notifications' frequency, content, and presentation interact.

[13] Harish Chetty, Monit Shah (2017) in their paper titled "**A Survey on Brain Tumor Extraction Approach from MRI Images using Image processing**". The proposed process Initially t2 weighted MRI images will be given as input. Then the pre-processing scheme will be done on the image by using an average filter the image will be smoothened. Skull stripping method is applied to remove the fatty tissue and skull in images. Watershed technique is used for segmentation. Erosion technique in morphological method is applied to detect tumor. This approach was Not suitable for large datasets.

[14] Hussna Elnoor Mohammed Abdalla, M. Y. Esmail (2018) in their paper titled "**Brain tumor detection using Artificial Neural Network**". The system is first provided with a brain MRI sample as input in the proposed process, and the image is then improved using the histogram equalisation technique. This method uses an image histogram to adjust the image contrast before segmenting the image using a global thresholding method and extracting features. By using Neuro fuzzy classifier, the image gets classified and shows the result as normal and abnormal. This approach has too much computation time and treats local pixels same as pixels for apart, sensitive to location of an object in an image.

[15] Yamini Sharma, Yogesh K. Meghrajani (2015) titled the paper as "**Brain Tumor Extraction From MRI Image Using Mathematical Morphological Reconstruction**". In this study, labelled MRI images that have been affected by impulsive noise were analyzed, and a method for locating brain tumours was proposed. A binary picture is created from a grayscale image using the global thresholding approach. Then, an operation known as "morphological

opening by reconstruction"—which involves two steps—is used. The first is erosion by a disc structural element (SE), and a morphological reconstruction makes up the second. The first phase's eroded image is used as a marker image for the second phase and offers a marker point at the tumour location. This morphological process creates a binary image with a tumour in the foreground, labels the image, and removes the salt noise. This method only eliminated noise.

3. PROPOSED METHODOLOGY

The primary goals of the study are to use Particle Swarm Optimization (PSO) to segment the MRI image and region-based convolutional neural networks (VGG16 and the DenseNet model) to predict the tumor. identifying many tumor kinds, including benign (non-cancerous) and its subtypes, such as adenomas and fibroids, as well as malignant (cancer). The BRATS 2019 dataset, which includes four MRI image modalities, is the one used in the proposed system.

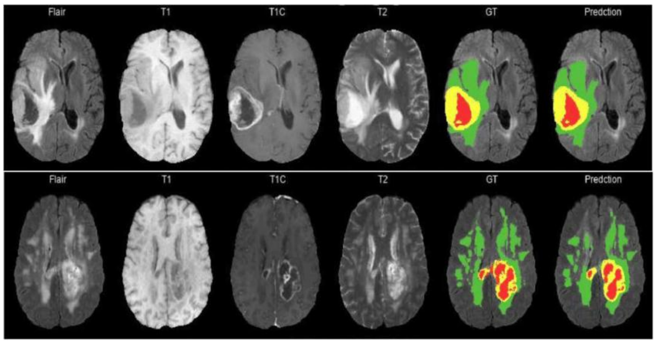

Fig 1: MRI Images of BRATS 2019

This model allows for the training of additional data. Using an optimization technique, the images are segmented to distinguish between normal and pathological cells. Following optimization, the dataset is trained to extract features and identify the type of tumor using the VGG16 and DenseNet models.

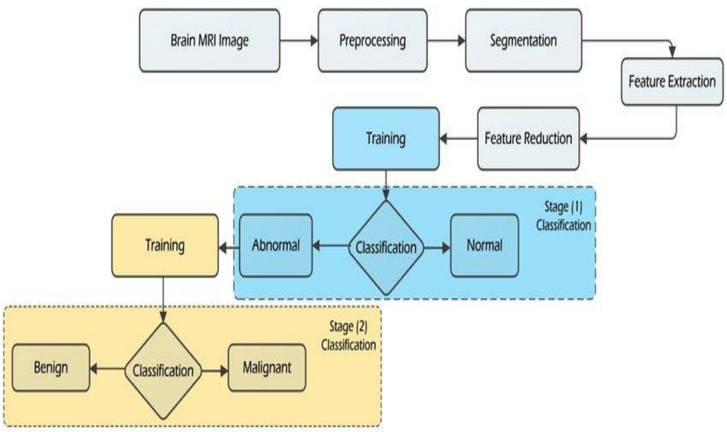

Fig 2: Overall Methodology

4. CONCLUSION

Since they are one of the leading causes of death among humans, brain tumors must be found early and treated. Basically, different image processing algorithms are applied to achieve this. In this study, we investigated two distinct methods for MRI image processing-based brain tumor detection. After reading the study, it is clear that the region-expansion technique is quite promising for the process's detection phase in the future. These two algorithms enable us to identify brain tumors using a variety of detection methods. Both image processing methods have a high rate of tumor identification success. However, both algorithms have some drawbacks that could be resolved by creating a new algorithm that considers a variety of factors and the comparison of the algorithms discussed in this paper.

ACKNOWLEDGEMENT

Special thanks to our team guide, G. Laxmi Deepthi, for all the technical support and guidance which led to the completion of the literature survey phase of the project with a good result in the end.

REFERENCES

[1] Shah, Hasnain Ali, et al. "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet." *IEEE Access* 10 (2022): 65426-65438.

[2] Rizwan, Muhammad, et al. "Brain tumor and glioma grade classification using gaussian convolutional neural network." *IEEE Access* 10 (2022): 29731-29740.

[3] Nawaz, Syed Ali, Dost Muhammad Khan, and Salman Qadri. "Brain Tumor Classification Based on Hybrid Optimized Multi-Features Analysis Using Magnetic Resonance Imaging Dataset." *Applied Artificial Intelligence* (2022): 1-27.

[4] Musallam, Ahmed S., Ahmed S. Sherif, and Mohamed K. Hussein. "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images." *IEEE Access* 10 (2022): 2775-2782.

[5] Noreen, Neelum, et al. "A deep learning model based on concatenation approach for the diagnosis of brain tumor." *IEEE Access* 8 (2020): 55135-55144.

[6] Sazzad, TM Shahriar, et al. "Development of automated brain tumor identification using MRI images." *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*. IEEE, 2019.

[7] Pereira, Sérgio, et al. "Brain tumor segmentation using convolutional neural networks in MRI images." *IEEE*

transactions on medical imaging 35.5 (2016): 1240-1251.

[8] Li, Ming, et al. "Brain tumor detection based on multimodal information fusion and convolutional neural network." *IEEE Access* 7 (2019): 180134-180146.

[9] Keerthana, T. K., and Sobha Xavier. "An intelligent system for early assessment and classification of brain tumor." *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*. IEEE, 2018.

[10] Jagan, A. "A new approach for segmentation and detection of brain tumor in 3d brain mr imaging." *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*. IEEE, 2018.

[11] Shen, Haocheng, and Jianguo Zhang. "Fully connected CRF with data-driven prior for multi-class brain tumor segmentation." *2017 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2017.

[12] Lavanyadevi, R., et al. "Brain tumor classification and segmentation in MRI images using PNN." *2017 IEEE International Conference on electrical, instrumentation and communication engineering (ICEICE)*. IEEE, 2017.

[13] Chetty, Harish, et al. "A survey on brain tumor extraction approach from MRI images using image processing." *2017 2nd International Conference for Convergence in Technology (I2CT)*. IEEE, 2017.

[14] Abdalla, Hussna Elnoor Mohammed, and M. Y. Esmail. "Brain tumor detection by using artificial neural network." *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)*. IEEE, 2018.

[15] Sharma, Yamini, and Yogesh K. Meghrajani. "Brain tumor extraction from MRI image using mathematical morphological reconstruction." *2014 2nd International Conference on Emerging Technology Trends in Electronics, Communication and Networking*. IEEE, 2014.