# Brain Tumor Detection Using Machine Learning With CNN Algorithm

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*Abstract*— Brain tumors are a major worldwide health concern, and effective treatment frequently depends on a prompt and precise diagnosis. Traditional methods of diagnosing brain tumors, such manually interpreting medical imaging, can be time-consuming and prone to mistakes made by humans. Machine learning algorithms have come to light as a potentially helpful tool to assist doctors in early diagnosis and classification of brain tumors. This article offers a novel method for brain tumor identification by utilizing machine learning techniques. The dataset used in this study consists of brain MRI (Magnetic Resonance Imaging) images from various sources, including cases with and without malignancies. In order to preprocess the data, we enhance the image quality and use a variety of machine learning techniques.

Keywords— CNN, Machine learning, MRI, Image Segmentation, Augmentation.

# I.INTRODUCTION

Primary brain tumors, which include both benign and malignant tumors, are a major contributor to cancer patients' morbidity and death. They also create disabilities, burden families, and place a financial strain on the healthcare system. A framework that makes use of MRI's automatic segmentation of brain tumors could improve diagnostic precision and provide a classification quickly. This led to the current study's focus on the automatic segmentation of brain tumors in MRIs by the use of small convolution kernels in multi-scale deep vs convolution neural networks.

Gliomas are the most prevalent kind of tumors in the human brain. Based on their cellular characteristics, gliomas are classified into two main groups: high-grade glioma (HGG), which is regarded as malignant, and lowgrade glioma (LGG), which is considered benign.

A medical imaging method called magnetic resonance imaging (MRI) is used in radiology to create images of the body's anatomy and physiological functions. MRI scanners use radio waves, powerful magnetic fields, and magnetic field gradients to create images of the body's organs. MRI is a non-invasive method that uses no ionizing radiation and does not include X-rays. These characteristics set magnetic resonance imaging (MRI) apart from other imaging modalities including computed tomography (CT) and positron emission tomography (PET) examinations.

Brain tumors are a dangerous and occasionally lethal medical condition. A correct diagnosis made in a timely manner is necessary for both effective therapy and good patient outcomes. The conventional methods of diagnosing brain tumors are labor-intensive and prone to human error since they rely on the manual interpretation of scan images from CT and MRI scans, for example. The application of machine learning techniques to medical imaging has led to an increase in the efficacy and precision of brain tumor diagnosis recently.

A branch of artificial intelligence called machine learning enables computers to recognize patterns in massive datasets and generate data-driven predictions. Machine learning algorithms can evaluate complex medical images, spot tiny irregularities, and help medical personnel make decisions when it comes to brain tumor diagnosis.

## **II. LITERATURE REVIEW:**

Segmenting a region of interest from an object is one of the hardest and most demanding tasks; separating a tumor from an MRI brain image is an ambitious endeavor. In order to replicate different diverse methodologies and obtain the best-segmented ROI from different perspectives, researchers from all over the world are working in this topic. These days, segmentation based on neural networks produces notable results, and the use of this approach. Yantao et al. [1] resembled Histogram based segmentation technique. Regarding the brain tumor segmentation task as a three-class Interpretability of machine learning models in medical applications is essential for gaining the trust of healthcare professionals. Researchers have developed methods to visualize and explain the decision-making processes of these models, providing insights into the features contributing to tumor detection. Tissue) classification problem regarding two modalities FLAIR and T1. The abnormal regions were detected by using a region based active contour model on FLAIR modality. The edema and tumor tissues were distinguished in the abnormal regions based on the contrast enhancement T1 modality by the k-means method and accomplished a Dice coefficient and sensitivity of 73.6% and 90.3% respectively.

Devkota et al. [5] established the whole segmentation process based on Mathematical Morphological Operations and spatial FCM algorithm which improves the computation time, but the proposed solution has not been tested up to the evaluation stage and outcomes as- Detects cancer with 92% and classifier has an accuracy of 86.6%. In [7], Brain tumor detection and removal have been suggested using a Fuzzy C-Means clustering technique, conventional classification algorithms, as well as a CNN to process 2D MRIs of the brain. Experiments were conducted using a real-time dataset consisting of tumor images of a variety of intensities, dimensions,

Pei et al. [8] proposed a technique which utilizes tumor growth patterns as novel features to improve texture based tumor segmentation in longitudinal MRI. Label maps are being used to obtain tumor growth modeling and predict cell density after extracting textures (e.g., fractal, and mm) and intensity features. Performance of the model reflected as the Mean DSC with tumor cell density.

In [9], development of clusters of results and its issues for categorization is squatted as along with ML methods, we also referred Data mining methods regarding security for our proposed mode [10].



**III. METHODOLOGY** 

Fig 1.Archintecuture of Proposed CNN Model.

In Figure 1, the architecture of the proposed model has been given. The brain lesion detection Process involves three essential phases. In Phase 1, the input image of the brain undergoes Preprocessing steps like resizing, normalization, and format conversion to prepare it for analysis. Noise Reduction techniques such as denoising filters are applied to enhance the image's clarity, while image enhancement methods like contrast adjustment and histogram equalization improve the visibility of brain lesions.

Phase 2 focuses on data preparation and dataset division. Brain imaging data, such as MRI scans, is collected, and the dataset is split into training, validation, and testing sets. The training set is used for model training, the validation set aids in hyper parameter tuning, and the testing set evaluates the final model's performance. In Phase 3, a convolutional neural network (CNN) model is designed, consisting of convolutional layers, pooling layers, and fully connected layers. Preprocessed

Brain images are fed into the CNN to extract meaningful features through feature mapping. The extracted features are then used to classify the presence of brain lesions, involving training the CNN

Model on a labeled dataset. Finally, the CNN model predicts the presence or absence of a brain lesion,

Providing a binary classification output of tumor or no tumor.

## **IV. PROPOSE SYSTEM:**

In our proposed work, the purpose of our proposed model is to build upon the current CNN-based image classification method, which includes Initialize GUI, segmentation, feature extraction and classification of MRI images, by correcting for its limitations: potential for computational load due to separate segmentation of normal brain image and tumor brain image [I], and potential for errors in classification due to pooling of image features. The framework, or skeleton, of our proposed model uses the steps and features of the current state-of-the-art model as its basis, but we implemented a DNNmodel based on an enhanced Conditional Random Field (CRF) algorithm with the aim of overcoming the slowness, and improving the precision, of brain tumor segmentation from MRI images as compared with the current state-of the-art method. In the end, our aim was to develop an automated brain tumor segmentation framework that makes easier the early diagnosis of brain tumors using MRI for medical personnel, enabling early intervention and follow-up to reduce mortality.

- I. Importing Libraries: The code begins by importing various libraries required for image processing, data manipulation, deep learning, GUI creation, and more.
- II. II. Class Definition: The `LCD\_CNN` class is defined. This class is responsible for creating the graphical user interface (GUI) and handling its functionality.
- III. III. Initializing the GUI: The GUI window's size, title, and other properties are set. A title label is created at the top. Buttons for "Import Data," "Train Data," and "Test Data" are created and positioned.
- IV. IV. Import Data Function: This function ('import data') is executed when the "Import Data" button is clicked. The data directory and the list of tumor patient data are initialized. Parameters for image size and slices are set. A message box informs the user that data has been imported successfully. The "Train Data" button is enabled, and the "Import Data" button is disabled.
- V. Train Data Function: This function ('train data') is triggered when the "Train Data" button is clicked. A convolutional neural network (CNN) model is defined using Keras. Convolutional, pooling, and fully connected layers are added to the model. The model is compiled with an optimizer and loss function. ImageDataGenerators are set up for training and validation data. The model is trained using 'fit generator'. The testing accuracy is evaluated and displayed. A message box informs the user that model training is successful. The "Test Data" button is enabled, and the "Train Data" button is disabled.



Figure 2. CNN Layers for the proposed model.

### V. RESULTS AND DISCUSSIONS

For the experimentation of the proposed CNN model, in this work we have considered the Kaggle dataset [25]. This dataset consists of brain tumor and healthy patient images. The dataset consists of 2513 brain tumor MRI images and 2084 healthy patient MRI images. The proposed model was coded in Python language and the was run using the Anaconda 3 platform. 🕴 Brain Turnor Detection



Figure 3. User Interface.

In Figure 3, the user interface for the brain lesion detection has been shown. The brain lesion detection interface consists of three boxes, import data, train data and test data. First, the complete Kaggle dataset consisting of the MRI images is imported which has been shown in Figure 4.



Figure 4. Importing Brian Images.

After importing, the dialog box appears which states "Data imported successfully." After the successful import of the dataset, the dataset is trained. By clicking on the train data, the dataset is trained.

The complete process of training has been shown in the Figure 5. During training the proposed CNN model is trained for 9 epochs. During training the proposed CNN model has attained an accuracy of 97.34% which has been shown in the Figure 6.

C:\Windows\System32\cmd.exe - python pbrain.py			
val_loss: 0.4490 - val_acc: 0.8202			^
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23/25 [	- acc.	0.0120	
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25/25 [====================================	- acc:	0.8388	
val loss: 0.1332 - val acc: 0.9495			
Epoch 16/30			
25/25 [====================================	acc: I	0.8467	- v
al loss: 0.1946 - val acc: 0.9416			
Epoch 17/30			
25/25 [	- acc:	0.8471	
val loss: 0.2089 - val acc: 0.9132			
Epoch 18/30			
25/25 [=======================] - 11s 450ms/step - batch: 12.0000 - size: 31.9200 - loss: 0.3318	- acc:	0.8521	
val_loss: 0.2061 - val_acc: 0.9243			
Epoch 19/30			
25/25 [=======================] - 10s 427ms/step - batch: 12.0000 - size: 31.9200 - loss: 0.3110		0.8647	
val_loss: 0.1824 - val_acc: 0.9322			
Epoch 20/30			
25/25 [======================] - 10s 421ms/step - batch: 12.0000 - size: 31.9200 - loss: 0.2630		0.8910	
val_loss: 0.1102 - val_acc: 0.9653			
Epoch 21/30			
20/20 f	0.0500		

Figure 5. Trained Model.



Figure 6. Model Accuracy.

For testing the proposed model, first, a random image is selected from the dataset which has been shown in the Figure 7. The selected figure would open and would be analyzed and compared with the dataset as shown in the Figure 7 and Figure 8. Finally, the output would be given as "Tumor Detected" or "No Tumor Detected" as shown in the Figure 10 and Figure 11.



Figure 9. Testing Model with Tumor image



Figure 10. Predicted Result.



Figure 11. Predicted Result.

### **VI. CONCLUSION:**

In the fields of neurology and neuroscience, brain lesion identification is crucial. Brain lesions are important markers of neurodegenerative illnesses, infections, tumors, and strokes that can help with prompt and precise diagnosis.

The existence of a brain lesions informs treatment planning, allowing medical personnel to decide whether to proceed with surgery, radiation therapy, medicine, or rehabilitation with knowledge. Furthermore, brain lesions offer important prognostic data that sheds light on the course and fate of the disease. It is easier to modify treatment plans and actions when lesions are tracked over time. Preventive measures are made possible by early brain lesion detection, which lessens the negative effects of conditions on patients' quality of life.

In order to increase accuracy, this work provides a Convolutional Neural Network (CNN) model for brain lesion detection utilizing MRI scans.

# VII. **R**eferences:

- Milan Acharya, Abeer Alsadoon, Shahad AI Janabi, P.W.C. Prasad, Ahmed Dawoud Yantao, "MRI-based Diagnosis of Brain Tumors Using a Deep Neural Network Framework." Published in 25th November 2020.
- [2] Parnian Afshar, Konstantinos N. Plataniotis, Arash Mohammadi Fellow, "BoostCaps: A Boosted Capsule Network for Brain Tumor Classification." Published in 20th July 2020.
- [3] M. Bharkavi Sandhiya, R. Tamilselvi, A. Nagaraj, M. Parisa Beham Fellow "BRAMSIT: A Database for Brain Tumor Diagnosis and Detection." Published in 28th February 2020.
- [4] Fatemeh Derikvand, Hassan Khotanlou Fellow "Patch and Pixel Based Brain Tumor Segmentation in MRI image using Convolutional Neural Networks." Published in 19th December 2019.
- [5] B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A. K. Singh, A. Elchouemi, "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction," 6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India..
- [6] Saddam Hussain, Syed Muhammad Anwar, Muhammad Majid Fellow "Brain Tumor Segmentation using Cascaded Deep Convolutional Neural Network." Published in 2017
- [7] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim and F. Muhammad Shah, "Brain Tumor Detection Using Convolutional Neural Network," 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 2019, pp. 1-6, doi: 10.1109/ICASERT.2019.8934561.
- [8] Ahmed S, Venigalla H, Mekala HM, Pei ,Dar S, Hassan M, Ayub S. Traumatic Brain Injury and Neuropsychiatric Complications. Indian J Psychol Med. 2017 Mar-Apr; 39(2):114-121. doi: 10.4103/0253-7176.203129. PMID: 28515545; PMCID: PMC5385737.
- [9] D A Nikam" cluster Based web search", published in International Journal of Advanced Research in Computer Science & Engineering ISSN-2277-9043, Vol-1, Issue-3, May 2012
- 10] Deepali kale, "Use of Data mining methods for secure privacy in social Networking sites", published International Journal Information Technology f management, Vol 12, Issued, February-2017, and ISSN 2249-4510.