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# Brain Tumor Detection Using Machine Learning with CNN Algorithm

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***Abstract: Brain tumors are a major global health issue, and successful treatment frequently depends on an early and precise diagnosis. Traditional methods of brain tumor detection, such as manual interpretation of medical images, can be time-consuming and prone to human error. Machine learning techniques have emerged as a promising approach to assist medical professionals in the early detection and classification of brain tumors. This study presents a novel method for brain tumor detection utilizing machine learning algorithms .The dataset used in this research comprises a collection of brain MRI (Magnetic Resonance Imaging)scans from diverse sources, including both tumor and non-tumor cases. We preprocess the data by enhancing image quality and for classification, different machine learning techniques are used, such as random forests, support vector machines (SVMs), and convolutional neural networks (CNNs).***
***Keywords: CNN, Machine learning, MRI, Image Segmentation, Augmentation.***

## I. INTRODUCTION

Primary brain tumors, which encompass both benign and malignant tumors, are a leading cause of morbidity and mortality in oncological patients, leading to disabilities and encumbering families as well as the health care system. A framework that capitalizes on automatic segmentation of brain tumors using MRI may increase diagnostic accuracy, and deliver a classification within a short time frame. The focus of the present study is, as a result, automatic segmentation of brain tumors in MRI using multi-scale deep versus convolution neural network with small convolution kernels. The most common type of tumors in the human brain is the gliomas tumors. Gliomas are divided into two main groups based on their cellular features: low-grade glioma (LGG) that is considered as benign and high-grade glioma (HGG) that is considered as malignant. Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form anatomical images and the physiological processes of the body. In order to produce images of the organs in the body, MRI scanners employ magnetic field gradients, strong magnetic fields, and radio waves. MRI is a non-intrusive system that does not include X-ray and does not use of ionizing radiation. These features distinguish MRI from other imaging techniques, such as computed tomography (CT) and Positron emission tomography (PET) scans. Brain tumors are a significant and life-threatening medical condition, with early and accurate diagnosis playing a crucial role in effective treatment and patient outcomes. The conventional methods of brain tumor detection, relying on manual interpretation of medical images such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, are not only time-consuming but are also susceptible to human error. In recent years, the integration of machine learning techniques into medical imaging has shown great promise in improving the efficiency and accuracy of brain tumor detection. Machine learning, a subset of artificial intelligence, empowers computers to learn patterns and make data-driven predictions from large datasets. In the context of brain tumor detection, machine learning algorithms can analyze complex medical images, identify subtle abnormalities, and assist medical professionals in making informed decisions. This paper explores the application of machine learning in brain tumor detection, aiming to highlight its potential in revolutionizing the field of neuroimaging.

## II. LITERATURE REVIEW

One of the most challenging as well as demanding task is to segment the region of interest from an object and segmenting the tumor from an MRI Brain image is an ambitious one. Researchers around the world are working on this field to get the best-segmented ROI and various disparate approaches simulated from a distinct perspective. Nowadays Neural Network based segmentation gives prominent outcomes, andthe flow of employing this model is augmenting day by day.

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 regionbased 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 mBm) and intensity features. Performance of the model reflected as the Mean DSC with tumor cell density.

## III. EXISTING SYSTEM

Detecting brain tumors using machine learning is a critical application in the field of medical imaging and healthcare. Several existing systems and approaches have been developed to aid in brain tumor detection and diagnosis. Here are some key aspects of the existing systems for brain tumor detection using machine learning:

1) *Medical Imaging Modalities:* Existing systems primarily rely on medical imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and sometimes positron emission tomography (PET) scans. These imaging techniques provide detailed information about the structure and characteristics of brain tumors.
2) *Data Collection:* Large datasets of medical images, both with and without tumors, are collected for training and testing machine learning models. These datasets may come from hospitals, research institutions, or publicly available sources.
3) *Preprocessing:* Image preprocessing is often a crucial step in these systems. It includes image resizing, normalization, noise reduction, and enhancement to improve the quality and consistency of the data.
4) *Feature Extraction:* Features are extracted from the medical images to represent the relevant information for the machine learning models. These features may include texture, shape, intensity, and statistical attributes of the tumor region.
5) *Machine Learning Algorithms:* Various machine learning algorithms are used for tumor detection and classification, such as: Convolutional Neural Networks (CNNs): These deep learning models are particularly effective for image analysis and can automatically learn relevant features from the data.
6) *Training and Validation:* Models are trained on a portion of the dataset and validated to ensure they can generalize to new, unseen data. Cross-validation techniques are often employed to assess model performance.
7) *Challenges:* Challenges in brain tumor detection systems include the need for large, highquality datasets, interpretability of machine learning models, handling class imbalance (as tumors are relatively rare), and addressing the risk of false positives and false negatives.

## 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 brainimage 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-ofthe-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.

1) *Importing Libraries:* The code begins by importing various libraries required for image processing, data manipulation, deep learning, GUI creation, and more.
2) *Class Definition:* The `LCD_CNN` class is defined. This class is responsible for creating the graphical user interface (GUI) and handling its functionality.
3) *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.
4) *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.
5) *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. Themodel 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.

## V. FUTURE WORK

This describes the execution of the proposed system in the detection of various diseases using CNN. The entire architecture depicts how the system deals with the recognition and detection of the test image, and below we explain the process of execution. The purpose of this research is to combine feature selection approaches with machine learning to identify pre-illnesses. For the early diagnosis of early diseases in MRI, CT scan, and X-ray images, this system makes use of deep learning techniques and image processing technology.

To make feature extraction more efficient, the dataset including defective images from several categories was preprocessed and segmented. Image Acquisition: In image acquisition, heterogeneous images of the medical dataset collected which contain subnormal and normal samples are gathered from a variety of individuals and converted into image format using a camera or some synthetic dataset.

1) *Pre-processing:* There may be difficulties like noise, image blurring, and other concerns since the input data samples were gathered from a range of people. As a consequence, preprocessing methods are used for images in order to reduce noise and improve image quality using modern techniques. Processing the image is tough due to the fact that it is originally in RGB color format. The RGB to greyscale conversion is required to reduce the complexity of a 3D pixel value to a1D value. Many applications, such as edge detection, do not benefit from the use of three-dimensional pixels.
2) *Feature Selection:* In image processing and data mining, feature selection is critical. It calculates the best subset of predicted characteristics from the original data. A subset of the original characteristics is chosen that retains enough information to distinguish successfully across classes. For feature selection, many search techniques can be utilized such as IG, PCA, and RAE.
3) *Feature Extraction:* There are six separate sets of photos taken, from various available datasets. The obtained images are then subjected to image processing methods in order to identify valuable information for future study. Because the gathered photos are of various sizes, it is necessary to transform them to a consistent size for effective preprocessing. The RGB photos are first scaled and transformed to Hue Saturation Intensity (HSI) format. Color perception is greatly aided by the use of HSI color space representation. Masking is then used to eliminate the pixels. Setting the pixel value of a picture to zero or another background value is known as masking. The diseased section of the original picture is then segmented using the K-means segmentation technique. The goal of segmentation is to transform a picture's representation into a meaningful image that is simpler to explore. The best characteristics from this dataset.

## VI. CONCLUSION

This project aims to leverage CNNs to improve the accuracy and efficiency of brain lesion detection from MRI images. By exploring the capabilities of deep learning in medical image analysis, this work contributes to advancements in automated diagnostic tools for healthcare professionals.

## REFERENCES


[1] 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] Amir, M.:Ali, T..:, Shaf, A.: Irfan, M.,: Saleem, M.Q. ML-DCN Net: Multi-level deep convolutional neural network for facial expression recognition and intensity estimation. Arab. N. Sci. Eng. 2020, 45, 10605160620.