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# Brain Tumor Detection Using CNN In Deep Learning

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**Abstract:** The human brain stands as the master controller of the intricate humanoid system. Anomalous cell proliferation within this vital organ can give rise to brain tumors, eventually progressing to the dire state of brain cancer. Within the domain of human health, the integration of Computer Vision emerges as a formidable ally, mitigating human error and furnishing precise diagnostic outcomes. Among the array of imaging modalities, including CT scans, X-rays, and MRI scans, magnetic resonance imaging (MRI) reigns supreme for its reliability and safety. Notably, MRI possesses the remarkable ability to discern even the most minute anomalies. Our research endeavors to explore diverse methodologies aimed at detecting brain cancer through the lens of brain MRI. Our approach involves meticulous preprocessing steps, employing techniques such as bilateral filtering (BF) to eliminate image noise, alongside binary thresholding and Convolution Neural Network (CNN) segmentation to accurately delineate tumor regions. Through the utilization of comprehensive training, testing, and validation datasets, we aim to leverage machine learning algorithms to predict the presence of brain tumors in subjects. Evaluation of our methodology will be conducted using a suite of performance metrics, encompassing accuracy, sensitivity, and specificity. It is our fervent aspiration that our proposed framework will outshine existing methodologies in the field, offering a novel and superior approach to the detection of brain cancer.

**KEYWORDS:** Brain tumor, Magnetic resonance imaging, Adaptive Bilateral Filter, Convolution Neural Network

## I .INTRODUCTION

Medical imaging encompasses the methodological and procedural aspects of generating visual representations of the body's internal structures for clinical scrutiny and medical intervention, along with depicting the functionality of specific organs or tissues. Its overarching objective is to unveil hidden internal structures obscured by skin and bones, facilitating both diagnosis and treatment of diseases. Additionally, medical imaging serves to establish a repository of normative anatomy and physiology, facilitating the identification of abnormalities. The processing of medical images involves computer-based manipulation, encompassing a spectrum of techniques and operations including image acquisition, storage, presentation, and communication. This processing aids in the identification and management of disorders, while also facilitating the creation of a repository cataloging the typical structure and function of organs for anomaly recognition. Utilizing electromagnetic energies such as X-rays and gamma rays, sonography, magnetic resonance imaging, endoscopes, thermal imaging, and isotope imaging, medical imaging encompasses both organic and radiological modalities. Although various technologies are employed to capture information about bodily location and function, they often exhibit limitations compared to imaging modalities that produce visual representations. Image processing techniques leverage computers to manipulate digital images, offering advantages such as flexibility, adaptability, efficient data storage, and communication. As different image resizing techniques continue to evolve, images can be managed effectively. Governed by sets of rules, image processing techniques enable synchronous operations on 2D and 3D images across multiple dimensions.

## II. LITERATURE SURVEY

In the dynamic landscape of medical image analysis, an array of ingenious methodologies has emerged, each striving to revolutionize the detection of abnormalities, particularly in the intricate realm of brain MRI imaging. These pioneering endeavors delve deep into the realms of clustering and classification algorithms, seeking to unlock the secrets hidden within the pixelated tapestries of MRI scans.Consider, for instance, the ground breaking work of Sivaramakrishnan and colleagues (2013), who deftly wielded the Fuzzy C-Means algorithm in tandem with histogram equalization to unveil the subtle contours of brain tumors. Their approach, akin to a digital artist delicately sculpting with pixels, achieved remarkable precision in delineating tumor boundaries, a feat crucial for accurate diagnosis and treatment planning. Similarly, the quest for perfection led Sufyan et al. (2015) to traverse the realm of enhanced edge detection, harnessing the power of Sobel feature detection to illuminate the subtle nuances of abnormal tissue. Their method, akin to a skilled cartographer mapping uncharted terrain, meticulously traced the intricate borders of tumors, offering clinicians a clearer vision amidst the MRI landscape. Venturing deeper into the labyrinth of image segmentation, researchers such as Sathya et al. (2011) embarked on an odyssey through the realm of clustering algorithms. Their journey, akin to intrepid explorers navigating uncharted waters, unveiled the potential of K-means and C-means algorithms in partitioning complex datasets, laying the foundation for more nuanced analyses. Meanwhile, Devkota et al. (2018) embarked on a quest for efficiency and accuracy, harnessing the power of morphological operations to unearth early-stage tumors from the depths of MRI imagery. Their approach, akin to skilled archaeologists delicately excavating ancient artifacts, unearthed hidden anomalies with surgical precision, offering hope in the battle against insidious diseases. But the quest for innovation did not end there. Sudharani et al. (2015) and Mahmoud et al. (2012) charted new frontiers with machine learning, employing K-Nearest Neighbor and Artificial Neural Networks, respectively, to decode the enigmatic language of MRI scans. Their endeavors, akin to master linguists deciphering ancient scripts, unlocked the secrets encoded within the pixelated glyphs, paving the way for more precise diagnoses. Yet, amidst this panorama of innovation, perhaps none have captivated the imagination quite like the advent of Convolutional Neural Networks (CNNs). Pereira et al. (2016), in their magnum opus of neural artistry, harnessed the untapped potential of CNNs to navigate the labyrinthine depths of brain imagery. Their creation, akin to a virtuoso painter crafting a masterpiece, breathed life into the static canvases of MRI scans, illuminating the path towards automated and reliable segmentation. In essence, the saga of medical image analysis is a testament to human ingenuity, a tale of relentless innovation and unwavering determination to unravel the mysteries concealed within the pixels. As researchers continue to push the boundaries of technological prowess, the future of medical diagnosis shines ever brighter, offering hope in the face of adversity and illumination in the darkest of corners.

## III.EXISTING SYSTEM

In the existing system for brain tumor detection, traditional methods such as magnetic resonance imaging (MRI) and computed tomography (CT) scans are primarily used. These methods involve capturing detailed images of the brain to identify any abnormal growths or tumors. The images obtained from these scans are then analyzed by radiologists or medical professionals to detect the presence of tumors.

**Disadvantages of Existing System:**

Limited Efficiency: Traditional methods can be time-consuming and may require significant time for image acquisition, processing, and interpretation. This can lead to delays in diagnosis and treatment, which may affect patient outcomes, especially in urgent cases.

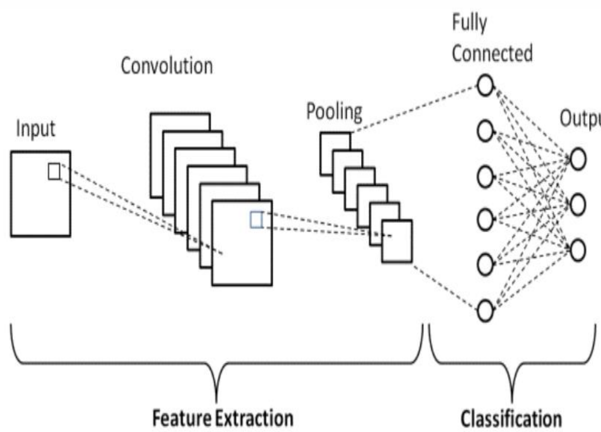
High Cost: MRI and CT scans are expensive imaging modalities, requiring specialized equipment and trained personnel to operate. This can lead to high healthcare costs for patients, particularly in regions with limited access to medical facilities.

Dependency on Human Interpretation: The interpretation of MRI and CT scan images relies heavily on the expertise of radiologists or medical professionals. Human error and variability in interpretation can lead to inaccuracies or missed diagnoses, potentially compromising patient care.

## IV PROPOSED SYSTEM:

The proposed system for brain tumor detection using Convolutional Neural Networks (CNNs) marks a significant leap forward in medical imaging technology. Leveraging the power of deep learning, CNNs are trained on vast datasets of brain MRI or CT scan images to autonomously learn patterns indicative of tumor presence. Through a series of preprocessing steps, model training, and feature extraction, the CNNs become adept at accurately classifying brain images as tumor-positive or tumor-negative. With the potential for real-time detection, automation, and scalability, this system offers a promising solution for improving the efficiency and accuracy of brain tumor diagnosis. By reducing the workload on radiologists and healthcare professionals while enhancing workflow efficiency, it holds the potential to revolutionize the diagnosis and management of brain tumors, ultimately leading to better patient outcomes and care quality.

**CNN ARCHITECTURE:**



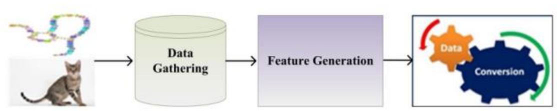




Fig1: data gathering feature generation

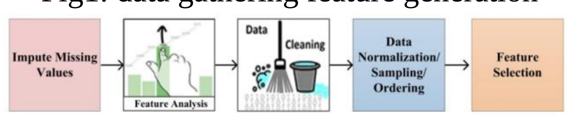



Fig2: preprocessing and feature selection

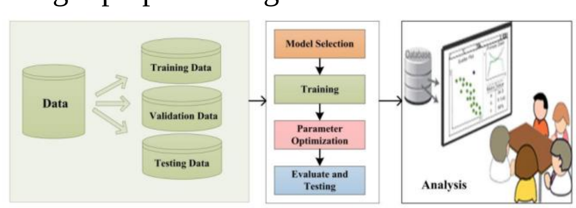



Fig3: data partitioning learning & evaluation

**DEFINITION OF CNN**

CNN, or Convolutional Neural Network, is a powerful tool for image classification tasks, particularly those involving three-dimensional images like RGB pictures. To handle large images more efficiently and prevent underfitting, input images are often downscaled. However, even with this downsizing, processing large images can still present challenges for CNNs.

The workflow diagram of a CNN outlines its design structure and optimization techniques in a reverse learning cycle. It breaks down how CNNs are organized, showing the convolutional layers, pooling layers, and fully connected layers, as well as the activation functions, loss functions, and optimization algorithms utilized. By dissecting the learning process from output to input, the diagram illustrates how the network's parameters are refined iteratively through backpropagation and gradient descent.

In essence, the workflow diagram of a CNN provides a concise overview of its architecture and training methods, shedding light on how CNNs extract features and classify images effectively.

**CONVOLUTION LAYER**

In the realm of image analysis, Convolutional Neural Networks (CNNs) play a pivotal role, utilizing filters or kernels to traverse across images in fixed intervals termed as strides. The stride size holds significant importance in achieving the desired outcomes. During the convolution operation, the filter interacts with portions of the image, computing the dot product, and summing up all values, which are then transferred to corresponding positions within the convolved feature map matrix. These filters vary in types and are adept at extracting diverse features from the input image. Adjustable parameters such as stride, padding, and the selection of filters are crucial in fine-tuning CNN's performance. Some common types of filters encompass Sobel filters, Laplace filters, blurring filters, and sharpening filters.

**Pooling Layer**

This layer conducts a process called max pooling, where a small kernel is applied to the image at a fixed stride. Its primary function is to select the pixel with the highest intensity within the kernel and discard the remaining pixels. As a result, the output matrix is a reduced-dimensional representation of the feature image. This reduction aids in eliminating unnecessary sparse cells within the image that do not contribute significantly to classification tasks.

Max pooling effectively reduces the dimensionality of the network or image, which can be beneficial for computational efficiency and memory usage. However, it is important to note that this reduction may lead to some loss of information. The underlying concept of max pooling is based on the assumption that adjacent or nearby pixels can be approximated by the pixel carrying the maximum information, thereby preserving the most relevant features while discarding redundant details.

**Activation Layer**

This layer predominantly employs the Rectified Linear Unit (ReLU) activation function. ReLU is characterized by its ability to set all negative values to zero while retaining positive values unchanged. Typically, this activation function is applied after the convolution and pooling layers. In various domains like Computer Vision, ReLU activations are increasingly recognized as state-of-the-art, achieving performance levels comparable to or even surpassing human capabilities.

Despite their effectiveness, designing a Convolutional Neural Network (CNN) remains a formidable task. Presently, there is no fixed formula for CNN design, and researchers often provide general guidelines which may not universally apply. The effectiveness of a CNN design is influenced not only by the algorithm but also by the nature and quality of the data. CNNs exploit the spatial hierarchical features present in data, extracting and classifying features into different categories.

To enhance CNN performance, techniques such as data augmentation and preprocessing have gained prominence. Data augmentation involves generating additional training samples by applying transformations like rotation, scaling, or flipping to existing data. This augmented dataset increases the diversity of training examples, facilitating better model training and mitigating the risk of overfitting. Ultimately, these practices contribute to the development of more robust models capable of generalizing well to new samples and effectively handling noise encountered during the training phase.

**Drop Out Layer**

The Dropout Layer is typically applied after the fully connected layer in a neural network, serving as a regularization technique. During each training iteration, the Dropout Layer randomly deactivates a fraction of input neurons, redistributing the weights among the remaining neurons. This process helps prevent overfitting by encouraging the network to rely on multiple pathways rather than becoming overly reliant on specific neurons. Common dropout rates range from 20% to 50%, and integrating a Dropout Layer often leads to a modest improvement in network performance, typically around 1% to 2%.

The Fully Connected Layer forms a pyramid-like structure from top to bottom, with the number of parameters gradually converging towards the desired number of output classes. Increasing the number of hidden units in this layer can enhance the network's capacity to learn, although there is a point of diminishing returns in terms of accuracy improvement. Selecting the optimal number of units is often an iterative process, relying on experimentation rather than a predetermined formula. These layers also contribute to the overall depth of the network, and it's common for networks in research to perform well with a number of units that are multiples of 64. Networks with two to three fully connected layers are typically effective, provided there are sufficient patterns being conveyed to the network following the flattening of outputs from the convolutional layers.

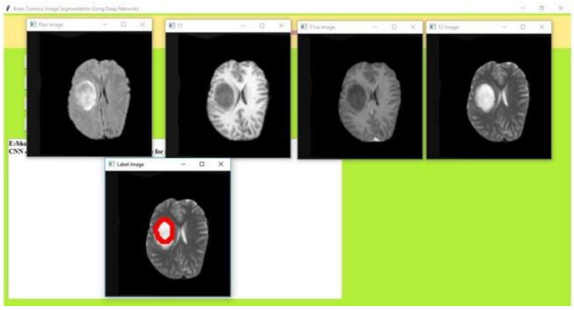
**Advantages of Proposed System:**

Enhanced Accuracy: The proposed system leveraging Convolutional Neural Networks (CNNs) offers superior accuracy in detecting brain tumors compared to traditional methods. By autonomously learning intricate patterns from vast datasets of brain images, CNNs can discern subtle features indicative of tumor presence with high precision.

Faster Diagnosis: With the automation provided by CNNs, the proposed system significantly reduces the time required for tumor detection. Rapid analysis of brain MRI or CT scans allows for expedited diagnosis, enabling timely interventions and treatment planning.

Reduction in Human Error: By minimizing the reliance on manual interpretation by radiologists, the proposed system mitigates the risk of human error in tumor detection. CNNs consistently apply learned algorithms to analyze images, ensuring more reliable and consistent results.

## V RESULT:




Brain Tumour Image Segmentation Using Deep Networks
Upload BRATS Dataset
Generate CNN & UNET Model
Upload Test Image & Segmentation
Dice Similarity Graph
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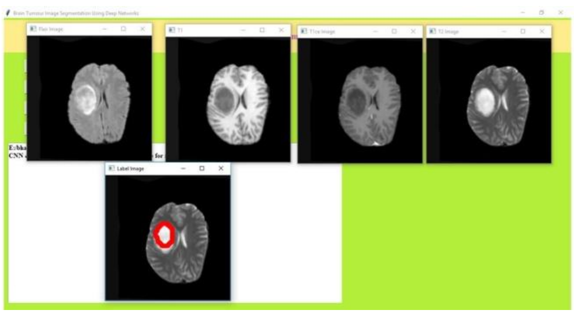
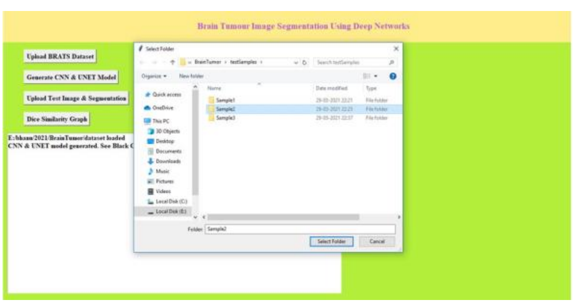
CNN & UNET model generated. See Black Console for model details




Brain Tumour Image Segmentation Using Deep Networks
Upload BRATS Dataset
Generate CNN & UNET Model
Upload Test Image & Segmentation
Dice Similarity Graph
Select Folder
BrainTumor › testSamples
Sample1
Sample2
Sample3
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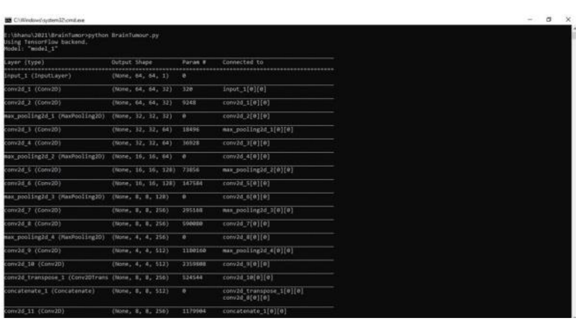
E:\bhanu\2021\BrainTumor>python BrainTumour.py
Using TensorFlow backend.
Model: "model_1"
Layer (type) Output Shape Param # Connected to
input_1 (InputLayer) (None, 64, 64, 1) 0
conv2d_1 (Conv2D) (None, 64, 64, 32) 320 input_1[0][0]
conv2d_2 (Conv2D) (None, 64, 64, 32) 9248 conv2d_1[0][0]
max_pooling2d_1 (MaxPooling2D) (None, 32, 32, 32) 0 conv2d_2[0][0]
conv2d_3 (Conv2D) (None, 32, 32, 64) 18496 max_pooling2d_1[0][0]
conv2d_4 (Conv2D) (None, 32, 32, 64) 36928 conv2d_3[0][0]
max_pooling2d_2 (MaxPooling2D) (None, 16, 16, 64) 0 conv2d_4[0][0]
conv2d_5 (Conv2D) (None, 16, 16, 128) 73856 max_pooling2d_2[0][0]
conv2d_6 (Conv2D) (None, 16, 16, 128) 147584 conv2d_5[0][0]
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conv2d_8 (Conv2D) (None, 8, 8, 256) 590080 conv2d_7[0][0]
max_pooling2d_4 (MaxPooling2D) (None, 4, 4, 256) 0 conv2d_8[0][0]
conv2d_9 (Conv2D) (None, 4, 4, 512) 1180160 max_pooling2d_4[0][0]
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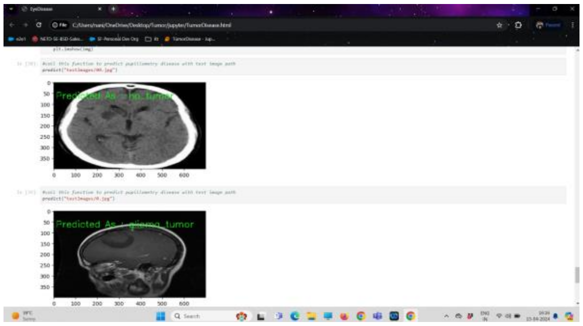

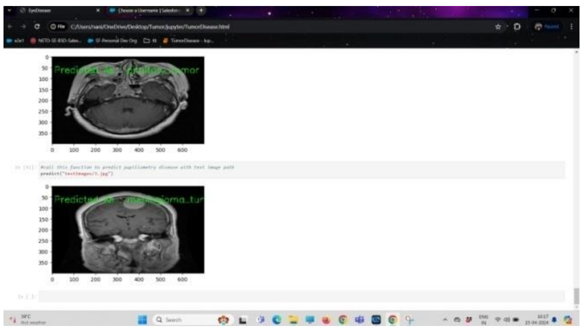

## VI. CONCLUSION

In summary, the implementation of Convolutional Neural Networks (CNNs) for brain tumor detection represents a transformative leap in medical imaging diagnostics. Offering unparalleled accuracy, accelerated diagnosis, and minimized human error, this system marks a substantial improvement over conventional approaches. Its scalability and seamless integration into established healthcare protocols further streamline processes, resulting in heightened efficiency and ultimately, enhanced patient care and outcomes. By harnessing the capabilities of artificial intelligence, this innovative system is positioned to redefine brain tumor detection, ushering in a new era of diagnostic precision and facilitating advancements in neuroimaging techniques and patient treatment strategies.

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