DESIGN OF DEEP LEARNING ALGORITHM FOR SEGMENTATION OF BRAIN TUMOR USING MAGNETIC RESONANCE IMAGES WITH CONTRAST DYE INJECTION

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Abstract

Medical imaging is progressing more quickly with the help of cutting-edge research and developments. Artificial Intelligence, deep learning, and virtual reality are key technologies of modern imaging applications. Hence, it is important to identify the necessary application level gaps and to develop a strategic model for performance improvements. One of the most prominent areas of medical imaging is brain tumor identification at an early stage. This paper presents the pre-and post-operative brain tumor segmentation for standard MR image scans. Also, it facilitates the newly developed "CdCnet" algorithm logic for contrast dye injection MR image scans. The brain tumor borders' visibility is less during and after the brain surgery due to tiny veins, which may impact the human body's functioning if it gets damaged during the surgery due to less visibility. Hence, contrast dye injection into the bloodstream helps the system to see arteries and veins. The proposed research methodology can be a new development for segmenting brain tumors of any grade.

Keywords: Medical imaging, MR images, contrast dye, segmentation, classification, registration

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1. Introduction

The latest conference was held on March 22, 2019, concerning the FDA, clinical researchers, pharmaceutic and biotech businesses, and clinical trials cooperative organizations to discuss difficulties and probable alternatives for advancing therapeutics for central nervous system metastases. They recognized the need for constant tumor measurement for dependable tumor response evaluation, incorporating the 1st stage of standard image acquisition through an MRI process that may become applied in multicenter research targeted at testing fresh therapeutics [1]. Irrespective of improved curiosity in using AI for pediatric brain tumor imaging, considerable obstacles to incorporation through clinical workflows can be found. The absence of interpretability natural to various AI solutions makes a “black box” all across AI that may provide physicians and patients with the trigger. Also, the regular development of AI methods brings about a need for constant analysis of effectiveness to safeguard patient security [2].

The latest segmentation algorithms will be suggested to conquer the redundancy issue of CNNs by determining each pixel with a class label. The CNN architecture is usually altered to a Fully Convolutional Network (FCN). It classifies every regional block in the image in a U-shaped architecture with contracting and growing pathways. Nevertheless, this approach needs many training pictures to produce exact segmentation, usually qualified by GPU memory. It likewise endures from extreme calculation time credited to pixel-wise calculations [3]. Recognition of brain tumors plays a crucial part in analyzing tumors and producing options on the subject of care and attention as per their grades. Many imaging methods will be used to recognize brain tumors even though, top rated to its superb image top quality and the fact that it depends upon no cosmic radiation, MRI is broadly used. Deep learning (DL) can be a computer vision research discipline and offers demonstrated amazing results presently, segmentation problems, particularly in category. This article offers a DL design centered on a Convolution Neural Network (CNN) to discover numerous choices of brain tumors leveraging two openly available assets or directories [4].

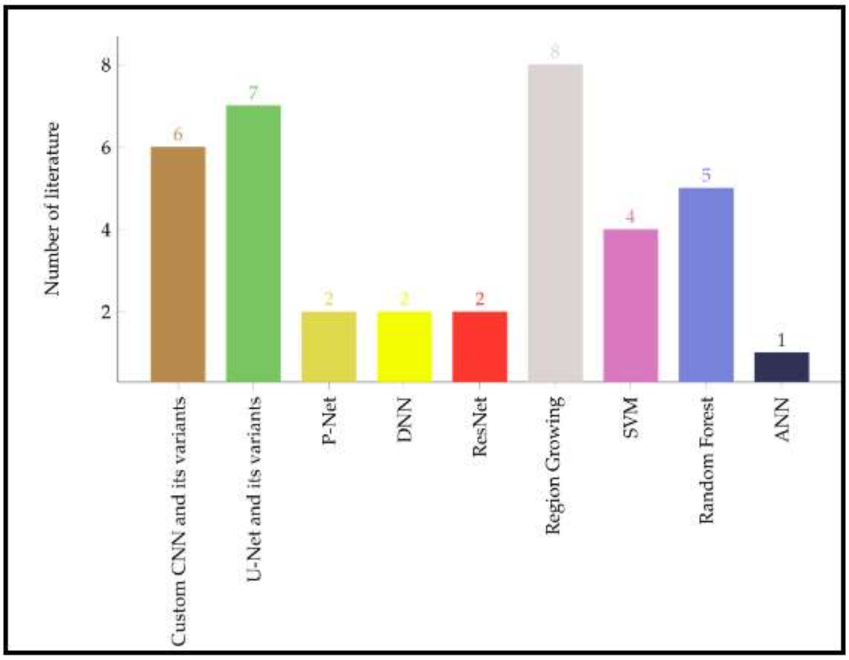

Fig.1: Various brain tumor segmentation methods (Erena Siyoum Biratu et al., 2021)

MRI is a fundamental modality generally applied in brain structure evaluation, seeing that it gives images with substantial comparison for smooth tissues and excessive spatial quality and examines unfamiliar wellness dangers. Furthermore, the radiologist produces four standard MRI image strategies for gliomas analysis: native (T1), post-contrast T1-weighted (T1c), T2-weighted (T2), and T2-weighted fluid-attenuated inversion restoration (T2-Flair) for every patient. After that, each region of glioma tumors requires to be segmented pixel-by-pixel cut before the 3D brain image is normally split up into four significant areas: the enhancing tumor (ET), the tumor core (TC), the whole tumor (WT), and regular tissues [5].

In computer vision, the LeNet architecture is one of the first types of CNN employed for manual digit acknowledgment. It includes two convolutional tiers, each of which is usually adopted through a sub-sampling (maximum pooling) coating to extract features. After that, they use two completely linked sheets as a classifier to extract features. In 2012, a team created a deep learning technique known as AlexNet; this model is usually the first large-scale CNN unit that results in the rebirth of deep neural networks for computer vision [6].

2. Literature review

From a clinical point of view, the aim of brain tumor diagnosis can be to effectively identify and localize tumor tissues from MRI images, applying well-researched clinical details and analysis features. The right clinical diagnosis should result in a well-timed and suitable disease cure. To accomplish this target, it is essential to get a clinical understanding and a data source symbolizing the data at a large level from which a decision and diagnosis can be produced. Manual brain tumor diagnosis is normally time-consuming and much less correct, credited to the range of tumor designs and designs, as there will be even more than 120 known types of brain tumors [7]. The author focuses on noise removal strategy, gray-level co-occurrence matrix (GLCM) features extraction and DWT-based brain tumor region developing segmentation to decrease the difficulty and enhance efficiency. This is adopted by morphological filtering, eliminating the noise that can be created after segmentation. The probabilistic neural network classifier was utilized to teach and check the functionality accuracy in detecting tumor areas in brain MRI images. The fresh outcomes accomplished almost 100% accuracy in determining regular and irregular tissues from brain MR images, showing the performance of the recommended procedure [8].

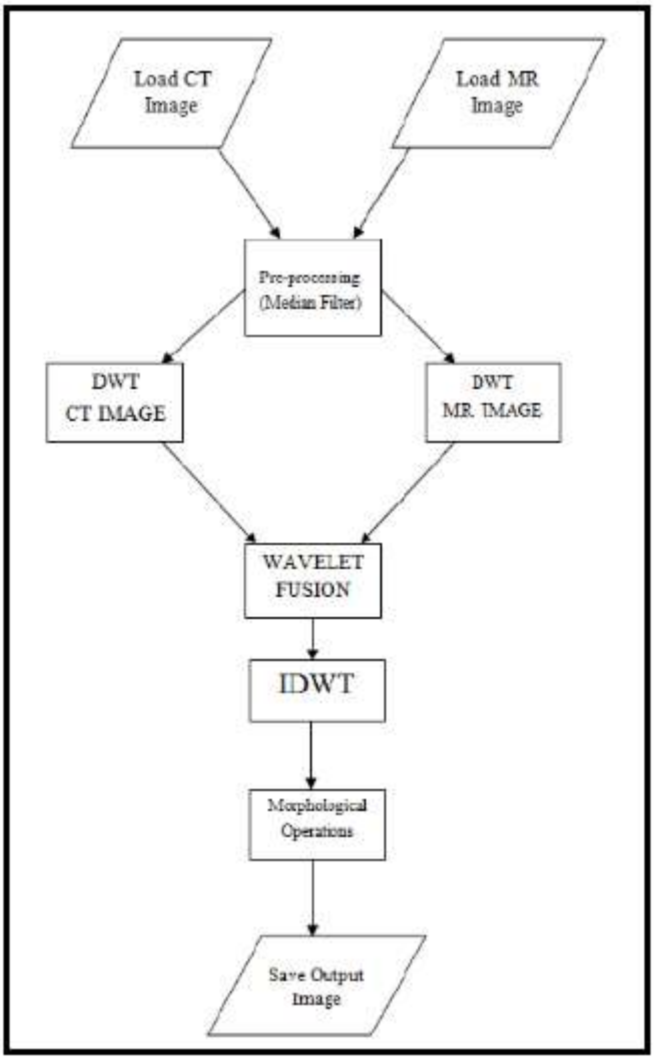

Fig. 2: DWT-Based brain tumor segmentation method (Varuna Shree, N., 2018)

As demonstrated in Fig. 3 below, the creator applied self-supervised learning by arbitrarily eliminating one modality during training to improve the model to manage the situations with an absent modality. While trained with a missing out on modality, the publisher employed an increased adversarial reduction to ensure the modal generated comparable features as in the full modality scenario. Somewhat than straight changing one domain to another in earlier strategies, we reflect on domain diversities from diverse channels [9].

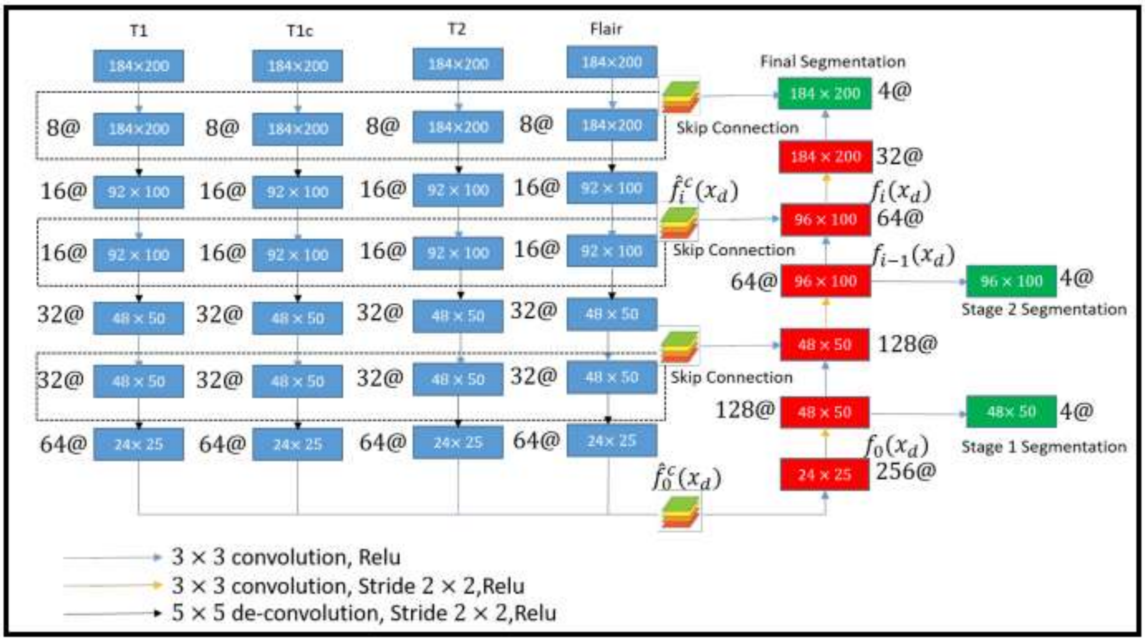

Fig.3: Four channel input segmentation network (Shen, Y. et al., 2019)

Relating to the author, working with automatic tumor segmentation could be feasible to forecast patients' survival. Two tasks will be concentrated: tumor segmentation in 3D-MRI images of brain tumor patients and survival prediction founded on these images. The author used a two-step strategy for the tumor segmentation: Initially, the tumor is based on implementing a 3D U-net. Further, another 3D U-net - even more complicated, but with a smaller sized field-of-view - picks up delicate variations in the tumor volume, i.e., it sections the placed tumor into the tumor core, improving tumor and peritumoral edema. The survival conjecture of the patients can be carried out with a somewhat basic, however correct algorithm that outperforms additional analyzed methods [10].

As per the author, the speed action of the level set was first engineered using a basic tolerance. The author described the number of fuzzy clustering strategies based on the basic fuzzy collection principle. The fuzzy c mean (FCM) algorithm assigns every pixel to the groupings with no label; nevertheless, the algorithm does not succeed in sectioning images with noise, images with the main strength difference, artifacts, etc. The author suggests a fully automatic and successful tumor segmentation centered on an SVM classifier and a wrapper-based genetic algorithm (GA). SVM classifier is utilized to classify the segmented region of the MRI image acquired by the block-included procedure. The image of the input is usually even used, adopted by extraction by utilizing texture features and histogram-based technique [11].

The author utilized the PNN Algorithm shown in Fig. 4 below for the image group approach structured on the Genetic Algorithm (GA) and K-Nearest Neighbor (K-NN) classifier for attribute selection, which is usually recommended. The searching features of genetic algorithms will be discovered for a suitable assortment of features from insight data and to get an ideal classification. The method is usually applied to classify and label brain MRI images into seven tumor choices. A multitude of texture features GLCM can get removed from an image, so selecting the greatest features to prevent poor generalization and over-specialization is usually very important. After that, the categories of the image and evaluation outcomes are established on the PNN algorithm [12].

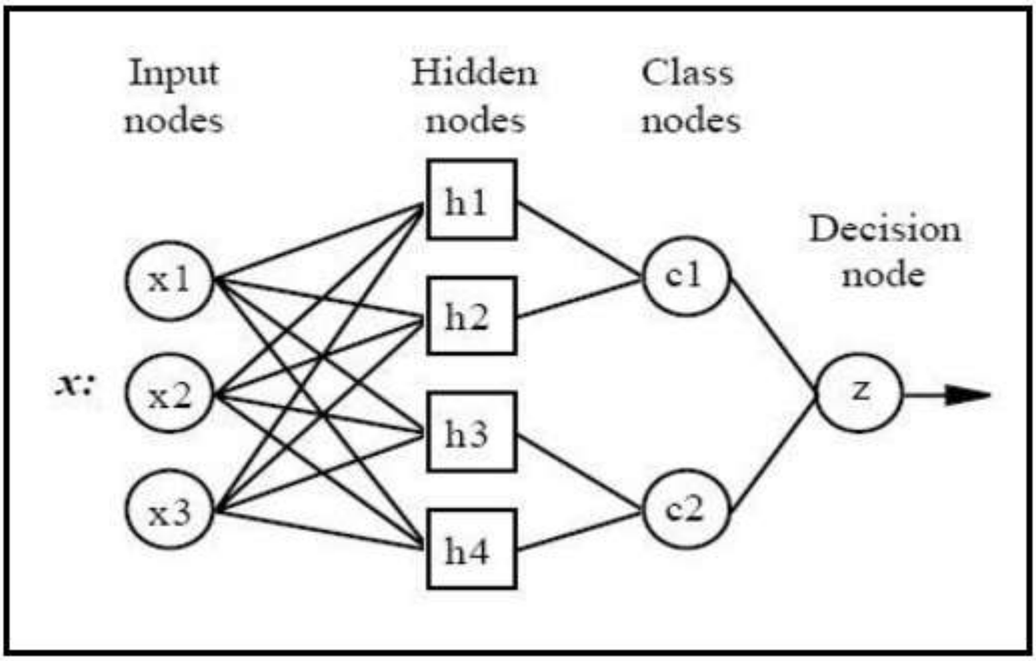

Fig.4: Probabilistic Neural Network Architecture (Azawi, R. M. et al, 2018)

The author suggested BrainTrawler, a task-driven, web-based platform with visual analytics solutions to check out heterogeneous neurobiological data. It helps spatial indexing to question large-scale voxel-level connection data and gene manifestation selections in the current. Relating data to the hierarchical structure of prevalent anatomical atlases allows the collection of diverse physiological amounts. Collectively, user-friendly network creation, iterative visual questions, and quantitative data enable the genetic dissection of multimodal networks on regional/global weighing scales in a spatial framework [13].

Two neglect connections were applied to raise the sum of facts available to the decoder part of the network. Skip links consider a collection of feature maps from the encoder and concatenate them with feature maps in the decoder. These associations enable a larger rate of recurrence tips to become straight re-introduced into the network and have been recently demonstrated to improve the accuracy for various segmentation duties. The author examined the network functionality with and without skipping out on relationships. Care was first used to stop the network from over-appropriate. This is especially required, credited to the fairly small volume of data obtainable for training. To this end, spatial dropout was used before maximum pooling and up-sampling levels. Spatial dropout is a variance of dropout, which can be even more relevant to CNNs. Spatial dropout will arbitrarily zeros out feature maps, making the network master uncover redundancy in determining essential image features instead of over-suitable to the peculiarities native to the training data [14].

The author assessed the usage of CycleGAN for data enhancement in CT segmentation responsibilities. We trained a CycleGAN to change distinction CT images into non-contrast images by applying a big image data source. The author, after that, utilized the trained CycleGAN to enhance our training by applying these artificial non-contrast images. The author opposed the segmentation effectiveness of a U-Net trained on the first dataset investigated to a U-Net trained on the mixed dataset of primary data and fabricated non-contrast images. The author considered the U-Net segmentation general performance on two individual datasets: The classic compare CT dataset on that segmentations had been produced and a second dataset from a diverse hospital comprising just non-contrast CTs [15].

Computerized segmentation of 3D brain tumors can conserve doctors' time and offer a correct reproducible answer for additional tumor evaluation and monitoring. Lately, deep learning-centered segmentation methods have exceeded classic computer vision methods for heavy semantic segmentation. CNN will be capable of discovering from good examples and demonstrating state-of-the-art segmentation accuracy both in 2D organic images and in 3D skilled image strategies. The author adhered to the encoder-decoder structure of CNN, with an asymmetrically huge encoder to extract deep image features, and the decoder component reconstructs compacted segmentation face masks [16].

3. Research Methodology

Brain Tumor is an abnormality growth arising from the brain tissues, which could be life-threatening if not detected and appropriately treated at an early stage. Typically, Magnetic resonance imaging (MRI) and Computer Tomography (CT) scans are used by medical staff to obtain detailed images of the brain for initial analysis over invasive procedures such as tissue biopsies. Further, computer-based image analysis, in collaboration with medical knowledge, can contribute significantly to early diagnosis. Hence, many researchers apply and validate an increasing number of existing and new computer-based image classification and segmentation algorithms in this study line [17, 18]. Accordingly, the following Fig. 5 shows the proposed methodology framework.

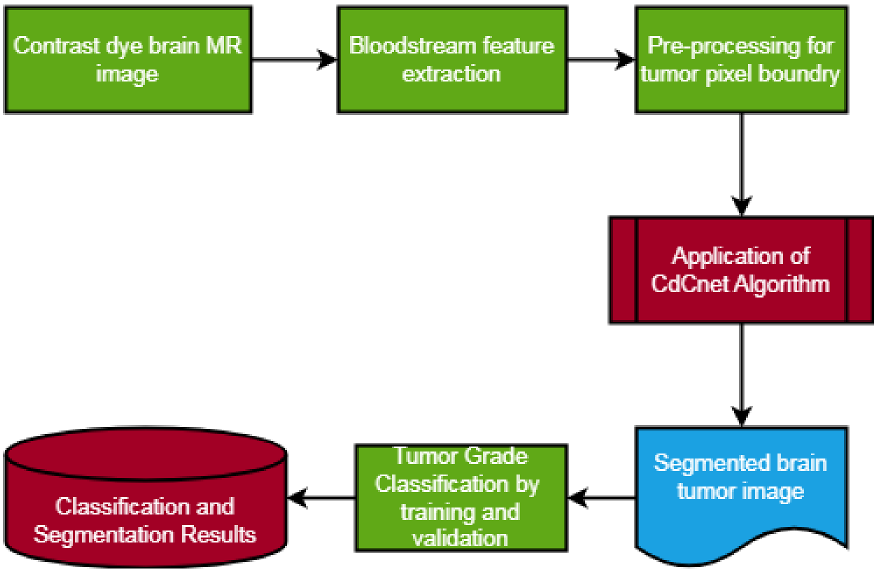

Fig.5: Proposed method flowchart (Generated by the Author)

In medical imaging, most existing work refers to automatically segmenting tumor regions in MR images. Recently, many researchers have presented different techniques to detect and segment the tumor region in MR images. After the tumor is segmented in MRI, it must be classified into different grades. The post-operative MRI often seems foggy due to the dripping of wounds. Consequently, the tiny brain veins are not visible to surgeons, and human error is possible. To reduce this risk, we proposed a new "CdCnet" algorithm, which facilitates segmentation and classification of brain tumor MRI when the contrast dye is injected to identify the bloodstream during the surgery and as a post-operative procedure. Unlike standard MRI, contrast dye injection provides visibility of bloodstreams in MRI.

As per the proposed framework shown in Fig. 5 above, the input contrast dye injected brain tumor MR image is fed. The core aim is to extract the structure of the bloodstream veins near the brain tumor borders, which can avoid human error during surgery. Further, during the pre-processing, the tumor border pixels can be extracted as an array of coordinated. Applying the proposed "CdCnet" algorithm segregates the bloodstream vein structure overlapping the brain tumor. Also, it considers the tumor border to provide segmentation using the CNN framework, and classification input is given to the training and validation of MR images. At last, the results are stored, which can be used by surgeons during and after the surgery. The proposed algorithmic logical execution is given below:

Algorithm: CdCnet

Input: Contrast dye brain tumor MR images
1. Array cdMR[], bStream[], btBorder[];
2. getcdMR(); //input the contrast dye brain tumor image
3. getbStreamCoordinates(); // identify the bloodstream vein structure
4. getbtBorder(); // extract the pixel border
5. OverFit(); // Overlapping structure of bloodstream pixels and tumor border pixels
6. IdentifyAdjecent(); // identify the adjacent pixels{
If (bStream[] != null && btBorder[]!=null)
Then
getbStreamCoordinates();
getbtBorder();
OverFit();
Else
IdentifyAdjecent()}
7. cdcnetTrain(); //Execute training of MRI

8. cdcnetValidate(); //Execute validation of MRI
9. segmentationResults[]; //Store segmentation results
10. classificationResults[]; // Store tumor grade classification
11. End

The proposed algorithm is tested for hyper-parameters accuracy, sensitivity and dice loss for epoch size 50.

4. Result Analysis

As discussed in the proposed methodology, the convolution neural network framework with the "CdCnet" algorithm has been executed with consideration of max pooling and ReLu function. The softmax with epoch sizes 50, 100, and 150 has been tested, and the optimum results are found at Epoch=50.

Table 1: Proposed CdCnet hyper-parameters results

Stage	**Analysis based on**	**Hyper Parameters**	**DBN+CNN**	**Proposed CdCnet**
Mid-operative	Standard MRI	Accuracy	79%	91.6%
		Sensitivity	80%	92.1%
		Dice loss	69.5%	30.3%
	Contrast dye MRI	Accuracy	80%	94.5%
		Sensitivity	80%	91.9%
		Dice loss	61%	27.7%
Post-operative	Standard MRI	Accuracy	79.6%	92.7%
		Sensitivity	76.5%	92.2%
		Dice loss	69.2%	32.5%
	Contrast dye MRI	Accuracy	78.1%	93.4%
		Sensitivity	75.3%	93.8%
		Dice loss	59.4%	29.1%

As per the comparative analysis, the proposed CdCnet model can reduce the dice loss, which implies the visibility of segmentation and accuracy enhancement of the classification during the training and validation.

5. Conclusions

In medical imaging, standard MRI scans are commonly used; however, the proposed research discussed the need for deep learning applications to analyze contrast dye MR images. The proposed CdCnet algorithm can be very useful for identifying bloodstream flow along the tumor borders so that during surgical procedures, surgeons can identify the pixel-level image segmentation, which can avoid human error. In the case of robotic surgery, the proposed algorithm can be used as a future plug-in for human-machine interfacing. They classify a brain tumor at an early stage and as a pre-and post-surgery gives a clear grade and leftover of the tumor, if any.

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