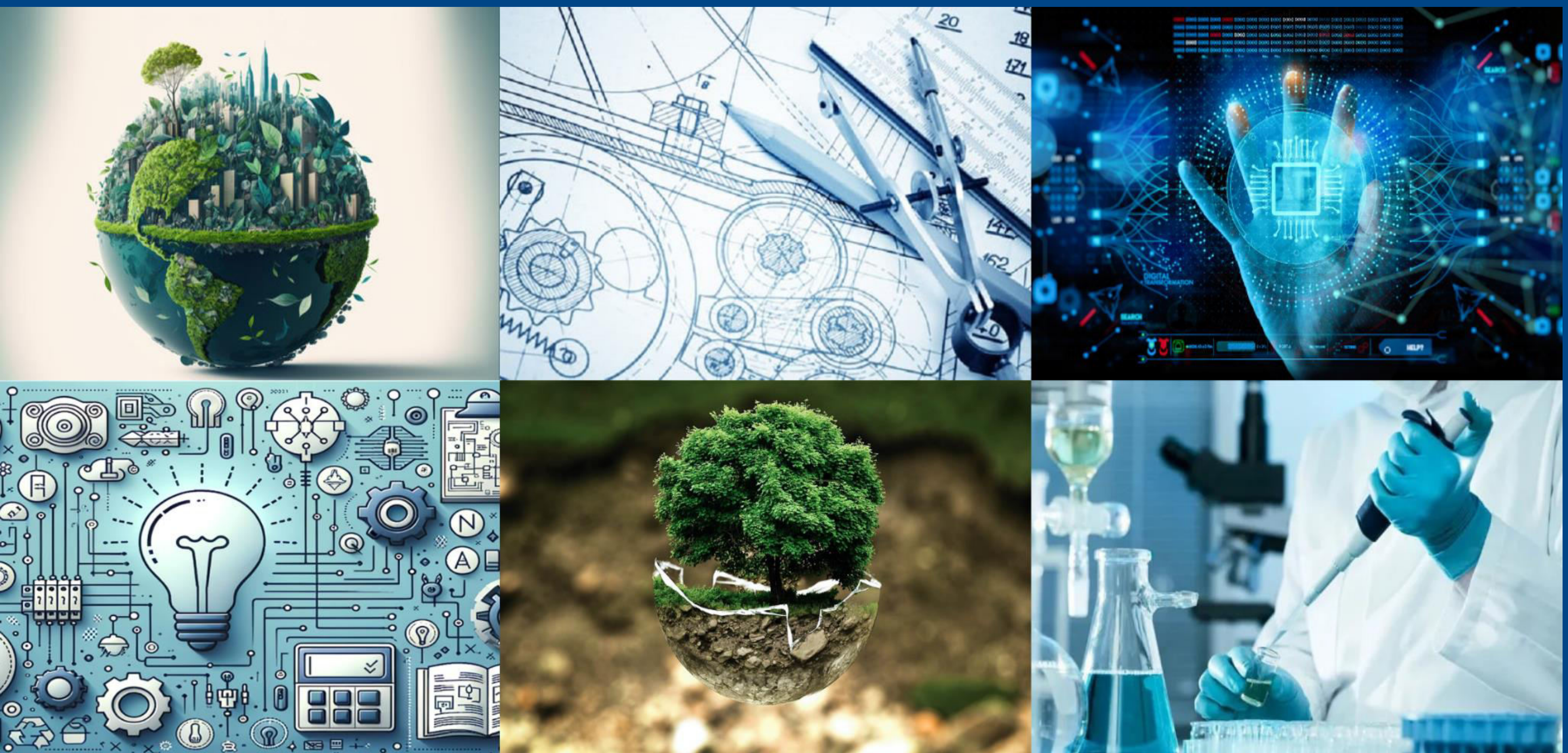
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 3, March 2025

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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Enhanced Brain Tumor Detection using Two-Pathway-Group CNNs: A Novel Deep Learning Framework

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ABSTRACT: Using magnetic resonance imaging to manually segment brain tumors for cancer diagnosis is a complex, tedious and time-consuming task. The accuracy and the robustness of brain tumor segmentation, therefore, are crucial for the diagnosis, treatment planning, and treatment outcome evaluation. Most automated brain tumor segmentation techniques use manually developed functions. Traditional deep learning methods (such as convolutional neural networks) also require a large amount of annotated data for training, which is usually difficult to obtain in the medical field. The proposed new model two-pathway-group CNN architecture for brain tumor segmentation, which exploits local features and global contextual features simultaneously. The model uses the equivalence of the bidirectional CNN model to reduce instability and overfit common parameters. Finally, we merge the cascaded architecture into a two-way multicast CNN, where the output of the basic CNN is processed as an auxiliary source and summarized at the final level. Validation of the models in the data sets BRATS2013 and BRATS2015 shows that the integration of this group CNN into a pathway architecture improved the overall performance over the currently published state-of-the-art while computational complexity remains attractive. To detected the Brain Tumor using Two-Pathway-Group Conventional Neural Networks. Use the traditional two-way cluster neural network for brain tumor detection.

I. INTRODUCTION

Tumors will have a huge effect on the brain. Brain cells are destroyed in the area affected by tumor gets and can cause brain collapse. The result of the tumor depends on the size and area affected in the brain. The Brain connected each and every part of the body together to make it perfect sense. If anything happens to the brain our whole system collapses. Some neurons in brain do not have capability to regenerate and there some neurons which stops regeneration as a person age. If the tumor is situated in any of that non- regenerative areas, a person might even lose one of his/her senses. Discovering the tumor at an early stage can save a person’s life. Artificial Intelligence is revolutionizing Healthcare in many areas such as Disease Diagnosis with medical imaging, Surgical Robot, maximizing hospital efficiency. Deep learning has been proven to be superior in detecting diseases from X-rays, MRI scans and CT scans which could significantly improve the speed and accuracy of diagnosis. Tumors are located and diagnosed through a very keen medical procedure. Magnetic Resonance Image (MRI) is one such process. We are going to train and validate our model on MRI. These images are sent into to model to train it to detect and locate brain tumor.

Segmenting brain tumors in multi-modal imaging data is a challenging problem due to unpredictable shapes and sizes of tumors. Deep Neural Networks (DNNs) have already been applied to segmentation problems and have shown significant performance improvement compared to the previous methods [4]. We use Convolutional Neural Networks (CNNs) to perform the brain tumor segmentation task on the large dataset of brain tumor MR scans provided by BRATS2015. CNNs are DNNs in which trainable filters and local neighborhood pooling operations are applied alternatingly on the raw input images, resulting in a hierarchy of increasingly complex features. Specifically, we used multi-modality information from T1, T1c, T2 and Flair images as inputs to different CNNs. The multiple intermediate layers apply convolution, pooling, normalization, and other operations to capture the highly nonlinear mappings between inputs and outputs. We take the output of the last hidden layer of each CNN as the representation of a pixel in that modality and concatenate the representations of all the modalities as features to train a random forest classifier.

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II. LITERATURE REVIEW

Magnetic resonance imaging (MRI) is widely used medical technology for diagnosis of various tissue abnormalities, detection of tumors. The active development in the computerized medical image segmentation has played a vital role in scientific research. This helps the doctors to take necessary treatment in an easy manner with fast decision making[1] . Brain tumor segmentation is a hot point in the research field of Information technology with biomedical engineering. The brain tumor segmentation is motivated by assessing tumor growth, treatment responses, computer-based surgery, treatment of radiation therapy, and developing tumor growth models. Therefore, computer-aided diagnostic system is meaningful in medical treatments to reducing the workload of doctors and giving the accurate results[2].

Brain tumor identification is really challenging task in early stages of life. But now it became advanced with deep-learning. Now a day's issue of brain tumor automatic identification is of great interest [3]. In Order to detect the brain tumor of a patient we consider the data of patients like MRI images of a patient's brain. Here our problem is to identify whether tumor is present in patients' brain or not. It is very important to detect the tumors at starting level for a healthy life of a patient [4]. There are many literatures on detecting these kinds of brain tumors and improving the detection accuracies. In this paper, we estimate the brain tumor severity using Convolutional Neural Network algorithm which gives us accurate results.

III. METHODOLOGY OF PROPOSED SURVEY

Existing systems describe the automation of cell segmentation. The technique is used to interactive multi label segmentation for N dimensional images. It segments the areas which are more difficult to segment. This method is iterative and provides feedback to the user as the segment is calculated.

CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other [5]. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are handengineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex.

Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cd over the entire visual area. The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. ConvNets need not be limited to only one Convolutional Layer. Conventionally, the first Cavalier is responsible for capturing the LowLevel features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network, which has the wholesome understanding of images in the dataset, similar to how we would[6].

MAGNETIC RESONANCE IMAGE (MRI)

The MRI is a diagnostic tool used for analyzing and studying the human anatomy. The medical images acquired in various bands of the electromagnetic spectrum. The wide variety of sensors used for the acquisition of images and the physics behind them, make each modality suitable for a specific purpose. In MRI, the pictures are produced using a magnetic field, which is approximately 10,000 times stronger than the earth's magnetic field. The MRI produces more detailed images than other techniques, such as CT or ultrasound. The MRI also provides maps of anatomical structures with a high soft-tissue contrast. Basically, the magnetic resonance of hydrogen (1H) nuclei in water and lipid is measured by an MRI.scanner. As the signal values are 12-bit coded, 4096 shades can be represented by a pixel. The MRI scanners require a magnetic field and it is available at 1.5 or 3 T. In comparison with the earth's magnetic field (~50 ft.) the magnetic field of a 3 T MRI scanner is approximately 60,000 times the earth field. The patient is placed in a strong magnetic field, which causes the protons in the water molecules of the body to align either in a parallel or anti-parallel orientation with the magnetic field. A radiofrequency pulse is introduced, causing the spinning protons to move out of the alignment. When the pulse is stopped, the protons realign and emit radio frequency energy signal that is localized

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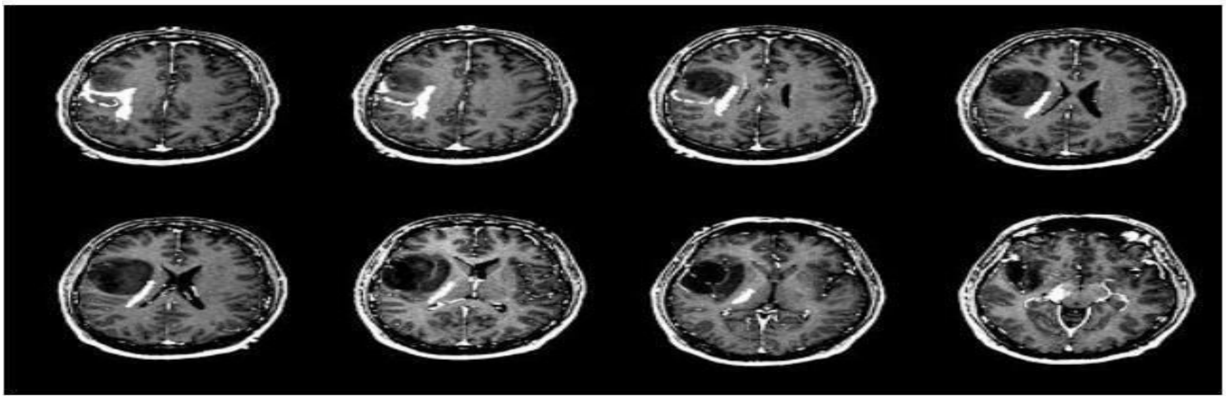
by the magnetic fields and are spatially varied and rapidly turned on and off. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is atechnique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution.



MRI of Human Brain

The most common method utilizes a technique called blood oxygen level dependent contrast. This is an example of endogenous contrast, making use of the inherent signal differences in blood oxygenation content. In the normal resting state, a high concentration of deoxyhemoglobin attenuates the MRI signal due to its paramagnetic nature. However, the neuronal activity, in response to some task or stimulus, creates a local demand for the oxygen supply, which increases the fraction of oxy hemoglobin causing a signal increase on T2 or T2*-weighted images. In a typical experiment, the patient is subjected to a series of rest and task intervals, during which MRI images are repeatedly acquired. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution. The signal changes during the course of time are then examined on a pixelby-pixel basis to test how well they correlate with the known stimulus pattern. The pixels that demonstrate a statistically significant correlation are highlighted in color and grayscale MRI image to create an activation map of the brain. The location and extent of activation is linked to the type of stimulus. Thus, a simple thumbfinger movement task will produce activation in the primary motor cortex.

The proposed method have various steps to predict the brain tumor as given below

- Image acquisition
- Image preprocessing
- Image segmentation
- Convolutional neural network
- Tumor detection

IMAGE ACQUISITION

The Primary Phase is acquiring images. After the Images collection, the obtained images have to be prepared with a wide range of vision. First capture the input images from available source

IMAGE PREPROCESSING

The images which are collected are subjected to pre- processing. In Pre- processing stage basic steps are image resizing and applying Gaussian filters for a perfect input clear image for easy identification of an image. Pre-processed images will be segmented digitally into various pixels. We do this segmentation for an image is to modify its representation to have more clarity to analyze the images.

IMAGE SEGMENTATION

In the first stage, the pre-processed brain Magnetic Resonance image will be transformed into a binary image with a threshold of 128 for the cutoff. Pixel values higher than the specified thresholds are mapped as white, with other regions marked as black; these two allow various regions to be generated around the disease. In the second stage, an

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erosion process of morphology is used to extract white pixels. Eventually, the eroded area and the original image are separated into two equal areas, and the region with black pixels from the eroding is counted as a mask of brain Magnetic Resonance image. In this paper, wavelet transformation is used for the efficient segmentation of the brain Magnetic Resonance image. Figure 3 shows the fully automatic heterogeneous segmentation. Figure 3(a) shows the axial image and its segmentation figure 3(b) Coronal image and its segmentation figure 3 (c) Sagittal images and its segmentation.

Extraction

In the feature extraction process, we can implement the effective texture operator which labels the pixels of an image. Here we extract the features and characteristics of Images for easy detection of brain tumor.

CLASSIFICATION

Convolutional neural networks algorithm is used for classification of brain images. It is producing the best results for the image

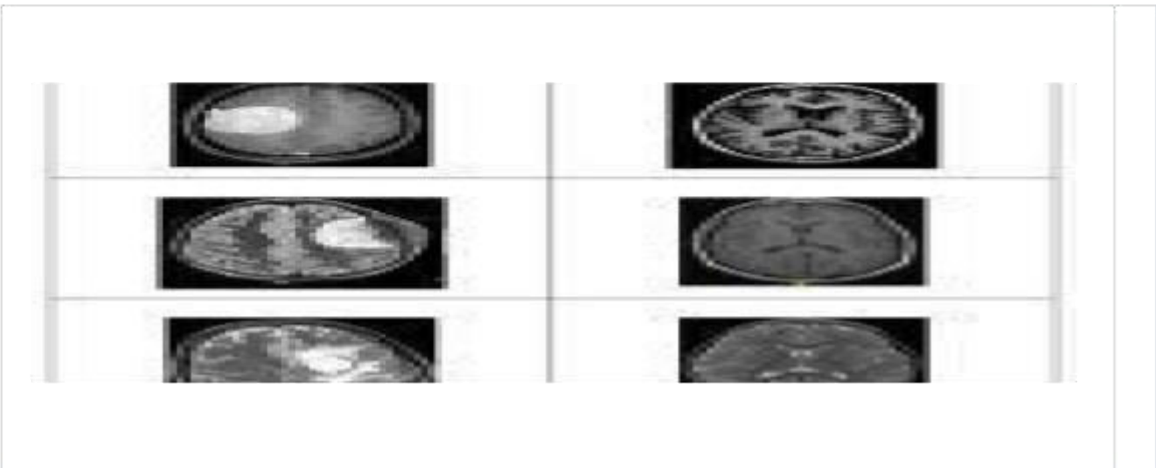
TUMOR DETECTION

Finally, analyze the image using filters and Convolutional neural networks algorithm to detect the tumor or Non-tumor.

IV.CONCLUSION AND FUTURE WORK

Our data set contains tumor and non-tumor MRI images obtained from various online sources. Use convolutional neural network for detection. Modeling is done using Python language. Calculate the accuracy and compare it with all other modern methods.

To determine the effectiveness of the proposed brain, training accuracy, verification accuracy, and verification loss need to be calculated. Tumor classification scheme. The current technology for detecting brain tumors uses SVM



(Support Vector Machine) classification. Feature extraction requires output. Based on the feature value, the classification output is generated and the accuracy is calculated. Tumor and non-tumor detection based on support vector machines take a long time and have poor calculation accuracy. The proposed CNN-based classification does not require a separate feature extraction step. The value of this function is taken from CNN itself. In the picture. The classification results of tumor and non-tumor brain imaging are shown. Therefore, the complexity and calculation time are low and accurate. The figure shows the results of brain tumor classification accuracy. Finally, according to the value of the probability score, it is classified as brain tumor or non- tumor brain. Normal brain imaging is the least likely. The score value compared with normal and neo-plastic brains.

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V. CONCLUSION

Our data set includes tumor MRI images and non-tumor images obtained from various online sources. Radiation podia contains real patient cases. Tumor images are obtained from the test data set of "Radio podia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015". The detection is carried out through a convolutional network. Modeling is done using Python language. Calculate the accuracy and compare it with all other modern methods. In order to determine the effectiveness of the proposed brain, training accuracy, verification accuracy, and verification loss need to be calculated.

Tumor classification scheme. The current technology for detecting brain tumors uses SVM (Support Vector Machine) classification. Feature extraction requires output. Based on the feature value, the classification output is generated and the accuracy is calculated. Tumor and non-tumor detection based on support vector machines take a long time and have poor calculation accuracy. The proposed CNN-based classification does not require a separate feature extraction step.

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