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A Research on Brain Tumor Detection using CNN Algorithm

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Abstract:
Brain Tumor segmentation is one of the most crucial and arduous tasks in the terrain of medical image processing as a human-assisted manual classification can result in inaccurate prediction and diagnosis. Moreover, it is an aggravating task when there is a large amount of data present to be assisted. Brain tumors have high diversity in appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes unyielding. The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI)and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate…etc. Especially, in this work MRI images are used to diagnose tumor in the brain. The classification of brain tumors is performed by biopsy, which is not usually conducted before definitive brain surgery. The improvement of technology and machine learning can help radiologists in tumor diagnostics without invasive measures. Brain tumor can be classified into two types: benign and malignant. Timely and prompt disease detection and treatment plan leads to improved quality of life and increased life expectancy in these patients. A machine-learning algorithm that has achieved substantial results in image segmentation and classification is the convolutional neural network (CNN). We present a new CNN architecture for brain tumor classification of three tumor types. The developed network is simpler than already-existing pre-trained networks.

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I. Introduction:

A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors-Malignant and Benign. Malignant brain tumors originate in the brain, grows faster and aggressively invades the surrounding tissues. It can spread to other parts of the brain and affect the central nervous system. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, are known as brain metastasis tumors. On the other hand, a benign brain tumor is a mass of cells that grow relatively slowly in the brain.

Brain and other nervous system cancer is the 10th leading cause of death, and the five-year survival rate for people with a cancerous brain is 34% for men and 36% for women. Moreover, the World Health Organization (WHO) states that around 400,000 people in the world are affected by the brain tumor and 120,000 people have died in the previous years. Moreover, an estimated 86,970 new cases of primary malignant and nonmalignant brain and other Central Nervous System (CNS) tumors are expected to be diagnosed in the United States in 2019.

The malignant tumors can quickly spread to other tissues in the brain and lead to worsening the patient's condition. When most of the cells are old or damaged, they are destroyed and replaced by new cells. if damaged and old cells are not eliminated with generating the new cells, it can cause problems. The production of additional cells often results in the formation of a mass of tissue, which refers to the growth or tumor. Brain tumor detection is very complicated and difficult due to the size, shape, location and type of tumor in the brain. Diagnosis of brain tumors in the early stages of the tumor's start is difficult because it cannot accurately measure the size and resolution of the tumor. However, if the tumor is diagnosed and treated early in the tumor formation process, the chance of patient's treatment is very high. Therefore, the treatment of tumor depends on the timely diagnosis of the tumor. The diagnosis is usually done by a medical examination, with computer tomography or magnetic imaging. MRI imaging is a method that provides accurate images of the brain and is one of the most common and important methods for diagnosing and evaluating the patient's brain. In the field of Medical Detection Systems

(MDS), MRI images provide better results than other imaging techniques such as Computed Tomography (CT), due to their higher contrast in soft tissue in humans.

The most common method for differential diagnostics of tumor type is magnetic resonance imaging (MRI). However, it is susceptible to human subjectivity, and a large amount of data is difficult for human observation. Early brain–tumor detection mostly depends on the experience of the radiologist. The diagnostics of the tumor could not be complete before establishing whether it is benign or malignant. In order to examine whether the tissue is benign or malignant, a biopsy is usually performed. Unlike tumors elsewhere in the body, the biopsy of the brain tumor is not usually obtained before definitive brain surgery . In order to obtain precise diagnostics, and to avoid surgery and subjectivity, it is important to develop an effective diagnostics tool for tumor segmentation and classification from MRI images.

Hence, early detection of brain tumors can play an indispensable role in improving the treatment possibilities, and a higher gain of survival possibility can be accomplished. But manual segmentation of tumors or lesions is a time consuming, challenging and burdensome task as a large number of MRI images are generated in medical routine. MRI, also known as Magnetic Resonance Imaging is mostly used for a brain tumor or lesion detection. Brain tumor segmentation from MRI is one of the most crucial tasks in medical image processing as it generally involves a considerable amount of data. Moreover, the tumors can be ill-defined with soft tissue boundaries. So, it is a very extensive task to obtain the accurate segmentation of tumors from the human brain.

The aim of this research is firstly to examine the classification of three tumor types from an imbalanced database with a CNN. Although considered large compared to other available MRI image databases, this database is still far smaller than databases generally used in the field of artificial intelligence. We wanted to show that the performance of the small architecture could compare favorably with the performance of the more complex ones. Using a simpler network requires fewer resources for training and implementation. This is a crucial problem to address because limited available resources make it difficult to use the system in clinical diagnostics and on mobile platforms. If the system is needed to be used in everyday clinical diagnostics, it should be generally applicable.

We wanted to examine the network's generalization capability for clinical studies and to show how the subject-wise cross-validation approach gives more realistic results for further implementation. In this paper, we present a new CNN architecture for brain tumor classification of three tumor types: meningioma, glioma, and pituitary tumor from T1-weighted contrast-enhanced magnetic resonance images.

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, and the flow of employing this model is augmenting day by day. Devkota et al. 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%. Yantao et al. resembled Histogram based segmentation technique. Regarding the brain tumor segmentation task as a three-class (tumor including necrosis and tumor, edema and normal 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.

III. Methodology:

Image Database:

There are three types of tumors: meningioma , glioma , and pituitary tumor . All images were acquired some patients in three planes: sagittal , axial and coronal plane. The examples of different types of tumors, as well as different planes . The number of images is different for each patient.

Image Pre-Processing and Data Augmentation

Magnetic resonance images from the database were of different sizes and were provided in int16 format. These images represent the input layer of the network, so they were normalized and resized to 256 × 256 pixels. In order to augment the dataset, we transformed each image in two ways. The first transformation was image rotation by 90 degrees. The second transformation was flipping images vertically . In this way, we augmented our dataset three times, resulting in some images.

CNN ALGORITHM

A convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types. A CNN is a kind of

network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.
There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice. This makes them highly suitable for computer vision (CV) tasks and for applications where object recognition is vital, such as self-driving cars and facial recognition.
Convolution Neural Network Model Layer:

1. Convolution 2D
2. MAX Poolig2D
3. Dropout
4. Flatten
5. Dense
6. Activation

➢ Convolution 2D: In the Convolution 2D extract the featured from input image. It given the output in matrix form.

➢ MAX Poolig2D: In the MAX polling 2D it take the largest element from rectified feature map.

➢ Dropout: Dropout is randomly selected neurons are ignored during training.

➢ Flatten: Flatten feed output into fully connected layer. It gives data in list form.

➢ Dense: A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.

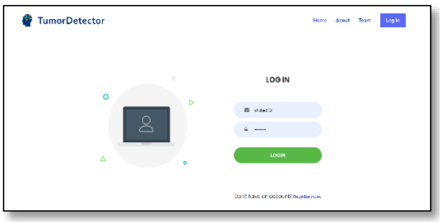
➢ Activation: It used Sigmoid function and predict the probability 0 and 1.

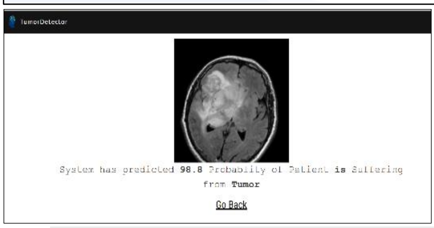
➢ In the compile model we used binary cross entropy because we have two layers 0 and

➢ We used Adam optimizer in compile model.

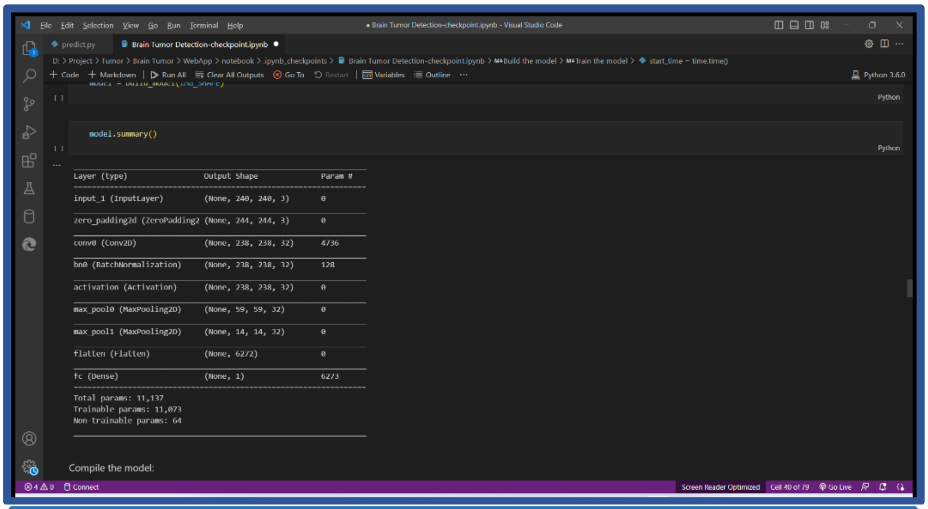
Adam - Adaptive moment estimation. It used for nonconvex optimization problem
like straight forward to implement.
▪ Computationally efficient.
▪ Little memory requirement

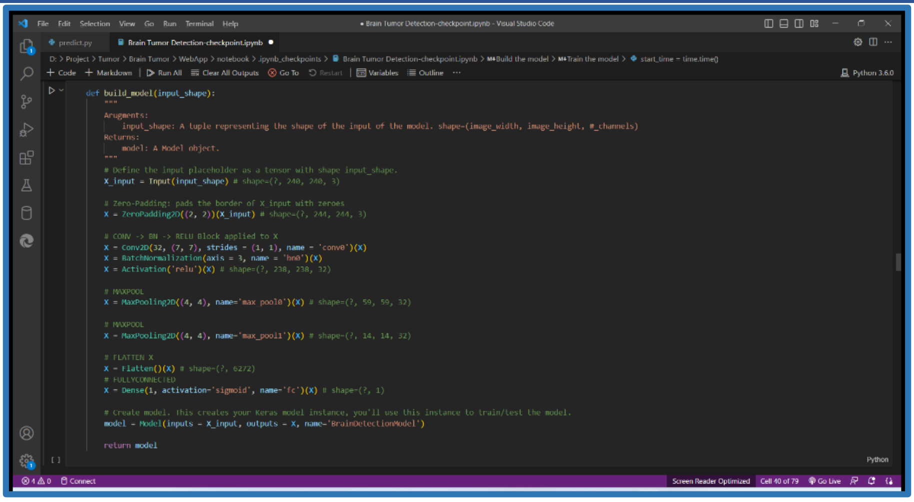
Work:
To develop the Software
Step 1-Gathering MRI data from various sources.
Step 2-Cleaning and pre-processing the MRI data.
Step 3-Segmenting the MRI images to isolate the brain tissue.
Step 4-Extracting features from the segmented brain tissue.
Step 5-Training the CNN model using the extracted features.
Step 6-Testing the accuracy and effectiveness of the software using a validation set of MRI images.
Step 7-Deploying the software for real-world use.

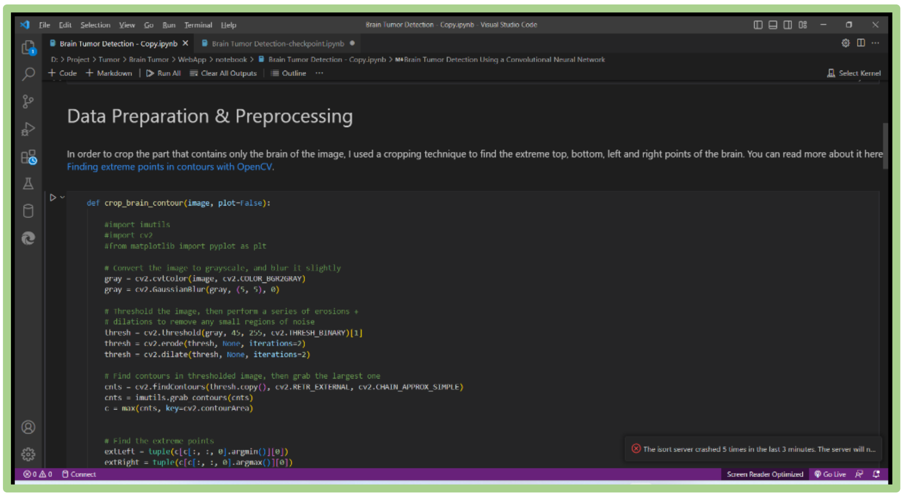




Different Models	Accuracy (%)
Seetha et al.	97.50
Tonmoy Hossain et al.	97.87
Our CNN model	**99.74**







IV. Conclusion:

The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. In the conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction and SVM and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme. Also, the classification results are given as tumor or normal brain images. CNN is one of the deep learning methods, which contains sequence of feed forward layers. Also, python language is used for implementation. Image net database is used for classification. It is one of the pre-trained models. So, the training is performed for only final layer. Also, raw pixel value with depth, width and height feature value are extracted from CNN. Finally, the Gradient decent based loss function is applied to achieve high accuracy. The training accuracy, validation accuracy and validation loss are calculated. The training accuracy is 97.5%. Similarly, the validation accuracy is high and validation loss is very low. The CNN is capable of detecting a tumor. The CNN is very useful for selecting an auto-feature in medical images. Images collected at the centers were labeled by clinicians, then, tumor screenings were categorized into two normal and patient classes. A total of 1666 images were selected as train data and 226 images were taken as a test data. The proportion of image categorization in two classes was proportional from the ratio of patients to healthy subjects. Images were applied to the CNN after preprocessing. In order to evaluate the performance of the CNN, has been used by other classifiers such as the RBF classifier and the decision tree classifier in the CNN architecture. The accuracy of the CNN is obtained SoftMax classifier 98.67% categorization. Also, the accuracy of the CNN is obtained with the RBF classifier 97.34% and the DT classifier 94.24%. In addition to the Accuracy criterion, we use the benchmarks of Sensitivity, Specificity and Precision evaluate network performance. According to the results obtained from the categorizers, the SoftMax classifier has the best accuracy in the CNN. The CNN has been able to categorize accurately 98.67% images in two normal and patient classes; and from a total of 226 images, three images have been constrained by the CNN. Using the proposed method of feature extraction and applying to the CNN. The accuracy of proposed method increased to 99.12% on the test data, which is an improvement compared to the traditional CNN. Due to the importance of the diagnosis given by the physician, the accuracy of the doctors helps in diagnosing the tumor and treating the patient increased high medical accuracy of the proposed method.

Methodology	Accuracy (%)
Seetha et al. [17]	97.50
Tonmoy Hossain et al. [18]	97.87
Proposed CNN model	**99.74**

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