International Journal of Research in Engineering, Science and Management
Volume 6, Issue 5, May 2023
https://www.ijresm.com | ISSN (Online): 2581-5792

Brain Tumor Classification using Deep Learning

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***Abstract*: The development of abnormal brain cells, some of which may turn cancerous, is known as a brain tumor. A magnetic resonance imaging (MRI) scan is the most common technique for finding brain tumors. Information about abnormal tissue growth in the brain can be discerned from MRI images. Misdiagnosis of a brain tumor will lead to ineffective medical intervention and lower patient survival rates. A proper treatment plan must begin with the accurate identification of a brain tumor in order to cure and prolong the lives of patients with this disease. Convolutional Neural Networks (CNNs) and computer-aided tumor detection systems have significantly advanced machine learning and offered breakthroughs. Many research papers use machine learning and deep learning algorithms to detect brain tumors. Brain tumor prediction takes very little time when these algorithms are applied to MRI images, and the higher accuracy makes it easier to treat patients. The radiologist can make quick decisions thanks to these predictions. seamlessly. This system ensures correct and authentic stem products. This proposed work presents a complete brain tumor detection, classification and diagnosis system with high accuracy (99.3%) that uses deep learning methods.**

***Keywords*: Brain tumor, Deep Learning, CNN.**

1. Introduction

MRI has emerged as a key tool in clinical studies of brain architecture [1]. Doctors can accurately diagnose specific diseases thanks to excellent resolution, contrast, and distinct soft tissue separation. Diseased and healthy tissues that make up the magnetic resonance image must be precisely segmented in order to identify pathology, evaluate evolutionary tendencies, prepare and select the best surgical technique or alternatives. Automated segmentation approaches are a useful solution as they enable automated volumetric analysis of the pathological MRI signal and assist management with inconsistent levels of automation [2]. A tumor in the body means the uncontrolled proliferation of cancer cells, while a tumor in the brain represents an abandoned growth of brain cells. While malignant (heterogeneous) tumors contain active (cellular) cells, benign brain tumors do not and share structural similarities with them [3]. Low-grade cancers such as meningiomas and gliomas are categorized as benign tumors, but high-grade tumors such as astrocytomas and glioblastomas are malignant tumors [4]. The most serious form of astrocytoma or glioma is called glioblastoma [5]. Because of the abnormally rapid development of blood vessels and the development of necrosis (dead cells) in most of the tumor, glioblastoma differs from all other forms of the tumor class. It is essential to separate diseased and healthy brain tissues using their respective subregions in MRI data for cancer treatment strategies and cancer research [6]. All medical image processing methods still rely on image segmentation, which involves removing regions of interest from images [7]. Due to the huge amount of data that each image provides, this technique is too time-consuming, laborious and sometimes difficult [8]. When segmenting images of brain tumors, the radiologist usually considers all these MRI methods simultaneously [9]. High inter-slice resolution and low inter-slice space is provided by typical acquisition techniques of clinical brain tumors. This creates another barrier to automated analysis. To overcome all these challenges, the new methodology that has been developed is clinically focused and takes into account not only advanced imaging technologies, the type of information that is usually available to patients and extensive clinical therapy plans.

2. Literature Review

The aim of this review section is to provide an overview of the literature on image segmentation techniques. The main goal is to show the advantages and limitations of different approaches. The key image processing techniques for brain MRI image segmentation are classified as k-means, SVM, FCM, k-nearest neighbor, neural network, adaboost, genetic and other methods, etc. Back propagation neural network (MLBPNN) machine learning based approach for classification brain tumors presented by P. Mohammed Shakeel et al. [10]. In addition, this technology can help doctors by scanning the image cell by coloring the attributes of the phone using order and package calculations. Acquisition, update and segmentation, extraction, image representation, characterization, and necessary management are just some of the different procedures required to create photos from biopsy images for disease identification. In this study, infrared sensor imaging technology is used to assess MLBPNN. Instead, the existence of a multidimensional neural evidence discriminating machine is drastically reduced when the entire structure is disrupted in some subsystems. This image sensor is connected to a wireless infrared imaging sensor that transmits heated

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tumor data to a medical professional to screen the patient's condition and effectively regulate the degree of ultrasound measurement, especially when there are elderly patients in remote areas. The local receptive field extreme learning machine (ELM-LRF) was developed by Ali ARI et al. [11] for the categorization and diagnosis of brain tumors. First, the noises were ignored using non-local means and local smoothing techniques. The second step involved classifying the malignant or benign nature of the cranial magnetic resonance (MR) images using ELM-LRF. The third phase involved tumor segmentation. This study exclusively used weight-weighted cranial MR images to achieve its objectives. In experimental studies, the classification accuracy of cranial MR images is 96.2%. The results of the analysis showed that the proposed strategy was more effective than previous recent literature research. It is a useful technique that can be used for computer-aided diagnosis of brain tumors according to experimental results. Deep wavelet Auto Encoder and Deep Neural Network (DWA-DNN) for brain magnetic resonance image categorization for cancer identification was proposed by Pradeep Kumar Mallick et al. [12]. In this study, a Deep Wavelet Auto Encoder (DWA) image compression method is proposed. It combines the transform wavelet image decomposition approach with the Auto Encoder key feature extraction function. The combination of the two has a significant impact on how few features are needed to maintain DNN identification. A brain image dataset was collected and the proposed DWA-DNN image classifier was investigated. The proposed method describes existing approaches and compares the effective criterion for DWA-DNN with other classifiers such as Auto Encoder-DNN or DNN. Tests of the DWA-DNN approach proposed to show that it is much more accurate and predictive than any other deep learning methodology. Further finding a way to combine DNN with many other improvements in Auto Encoder would be much more interesting to see the impact or results within a brain MRI dataset [13]. Rasel Ahmmed, Anirban Sen Swakshar, Md. Foisal Hossain and Md. Abdur Rafiq proposed an approach that includes steps such as image preprocessing, segmentation, feature extraction, SVM classification, and tumor stage classification using artificial neural networks [14]. (ANN). Three contrast enhancement approaches are used in the preprocessing stage: adjusted, adaptive thresholding, and histogram display using the weiner2 and median2 filters. For segmentation, the TKFCM algorithm is used, which combines K-means and Fuzzy c-means with minor modifications. Features are extracted in two different orders. Feature-based statistics are generated for both first- and second-order regions. The SVM then classifies the brain MRI as normal or tumorous. ANN classifier is used to categorize brain tumor stage. The amount of information used for each typical MRI image. The number of data used for each normal brain, malignant tumor, and benign tumor MRI image is obtained from 39 images, where 3 normal, 9 benign, 17 malignant I, 6 malignant II, 3 malignant II, and 1 malignant stage IV tumor MRI brain images. The accuracy of the proposed method is 97.44%.

Seetha, J. and S.S. Raja proposed a method for automatic diagnosis and classification of brain tumors based on deep CNN [15]. Fuzzy C-Means (FCM) is the basis of the brain segmentation system, and texture and shape features were collected from these segmented regions, which were then fed into SVM and DNN classifiers. The results showed that the method has 97.5% accuracy. The opposite is true for Cheng, Jun et al. For the categorization of brain tumors, Sajjad, Muhammad et al. [16] proposed a comprehensive data augmentation strategy combined with CNN. using MRI scans of segmented brain tumors to classify brain cancer into multiple grades. With transferee learning and a pre-trained VGG-19 CNN architecture, they were able to classify the data with an overall accuracy of 87.38% and 90.67% for pre- and post-augmentation data, respectively. Using a modified version of AlexNet CNN, Khawaldeh, Saed, et al. [17] proposed a system for the non-invasive classification of glioma brain tumors. Whole brain MRI scans were used for the classification process and the labels applied to the images were applied at the image level rather than at the pixel level. The results of the experiments showed that the technique has a respectable performance with an accuracy of 91.16%.

3. Background

A. Dataset

The brain tumor dataset suggested by Cheng, Jun, et al. is used in this paper and is freely accessible online at https://figshare.com/articles/brain tumor dataset/1512427/5. The dataset includes 3064 brain MRI images that are T1 weighted and contrast-enhanced and are divided into three classes: glioma, meningioma, and pituitary tumor. These data were obtained from 233 patients.

Table 1
Image dataset summary

Class	Number of images
Glioma	1426
Meningioma	708
Pituitary Tumor	930
Total	3064

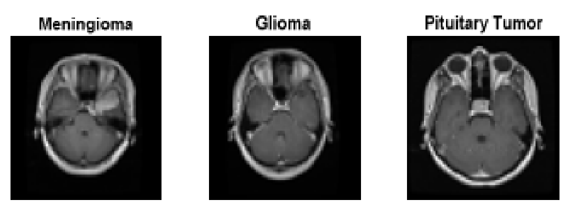

Fig. 1. Sample pictures from the dataset

B. Methodology

The most popular deep feed forward neural network at present, which can process different types of data inputs such as 2D images or 1D signals, is a convolutional neural network (CNN). A convolutional neural network (ConvNet/CNN) is a deep learning algorithm that can analyze an input image, rank distinct image features by relevance, and distinguish between them. Relatively speaking, ConvNet requires significantly less preprocessing than other classification techniques. ConvNets have the capacity to learn these filters and properties, whereas in primitive techniques the filters are created manually. Input layer, convolutional layer, RELU layer, fully connected layer, classification layer and output layer are many layers that generally make up a CNN. The basis of CNN is a convolution using a trainable filter with a predetermined size and weight, which are adjusted during the downsampling process in the training phase to achieve high accuracy. In this study, photographs of excised and unexcised brain tumors are stored in a database and organized into three folders, each containing photographs for a specific class of glioma, meningioma, or pituitary tumor. The database is divided into training and testing data, with 70% of the data used in training and the remaining 30% used in testing. A novel CNN architecture is used in this study. The structure of the proposed CNN architecture will be explained in the following sections.

4. Proposed Method

Deep learning has recently gained popularity due to its high accuracy rate and wide range of applications in many research fields, including computer vision, image processing, authentication systems, and speech recognition. CNNs are feedforward artificial neural networks (ANNs) inspired by biological processes designed to recognize various patterns directly from image input. Motivated by the recent success of CNNs in a number of difficult tasks, we have thus proposed and applied a newly created CNN architecture in this work. The entire process includes data augmentation, data preprocessing, where images are cropped to the optimal size and then processed by our neural network architecture, which contains many layers.

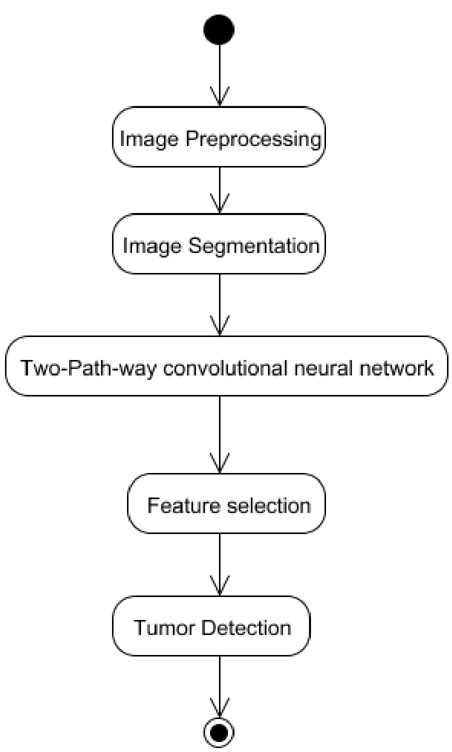

Fig. 2. Proposed workflow of the application

A. Image Preprocessing and Segmentation

This study uses MRI (Magnetic Resonance Imaging) images of several patients, which are read in the form of a .mat file. This dataset combines photographs of the brain with and without tumors. 90% of the original dataset, which contained photographs free of tumors and high- and low-grade gliomas, is included in the training dataset. 10% of the original data set is used as a test data set and the accuracy of the model is calculated using this data. .mat files are converted to readable format and in our case, they are converted to .jpg format. The images are ready for the algorithm to work with the image data—more specifically, the pixel values—to identify the tumor in that image during this preprocessing step. Image enhancement involves adjusting the brightness or contrast of the image to improve the clarity of the image for analysis. By default, RGB format is used to read all photos. Photos must first be converted to grayscale format because processing RGB images requires providing a large amount of information for each pixel, but processing grayscale images requires less information for each pixel. Denoising the photos allows us to get good image quality, which improves the performance of the model. Multiple filters can be used for this, including a median filter. Because it reduces noise with significantly less blurring than other filters, the median filter is very popular. A median filter replaces each pixel's value with the result of applying the median to neighboring pixels as it moves from one pixel in the image to the next. To ensure that the model is trained on consistent data without any variations that could mislead it, all photos are rescaled to the specified dimension.

B. CNN Architecture

Each layer in a neural network has three components. The input layer is the first layer, the hidden layer is the second layer, and the output layer is the third layer. The number of nodes in each layer is usually a power of two to maintain the symmetry of the entire model. An edge connects nodes of one layer to nodes of another layer. And this edge is assigned a weight that shows the importance of this node in the conclusion of the network. The result is calculated for each node by summing the product of the input nodes and the weights assigned to them. The sum is then given an activation function and the node result is calculated.

When working with photos, the data is typically enormous, and if it is fed to the model in an up-to-date form, the model will become cumbersome, the training process will take a long time, and the memory requirements will be high. So a convolutional neural network is used. The input layer of a convolutional neural network receives preprocessed data. A filter is used to reduce the dimensions of the input data when reading the preprocessed data.

By using max-pooling or min-pooling, we can further reduce the data. The procedure we'll use to move forward is known as forward propagation, and it's the same procedure we used for neural networks. We calculate the difference in error between the expected and forecast results. The weights are then appropriately updated to provide the desired result. This procedure is also called error backpropagation.

C. Feature Extraction

The process of extracting essential information from medical images that may be utilized to precisely differentiate between various tumor types is a crucial step in the categorization of brain tumors. 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.

Some of the useful features can be found below in the mathematical formulas.

Mean: To find the mean of an image, divide its total pixel value by the sum of all of its individual pixels.

$$N = \left(\frac{1}{n\times m}\right)\sum_{y=0}^{n-1}\sum_{x=0}^{m-1} f(y,x)$$

Standard Deviation: The SD is the second central moment that enables a probability distribution to be specified for an observed population. Better value depicts an image's edges with a high degree of contrast and intensity.

$$SD(\rho) = \sqrt{\left(\frac{1}{n\times m}\right)\sum_{y=0}^{n-1}\sum_{x=0}^{m-1}(f(y,x) - N)^2}$$

Contrast: It's a calculation of the intensity and the neighbor of a pixel over an image

$$G = \sum_{y=0}^{n-1}\sum_{x=0}^{m-1}(y - x)^2 f(y,x)$$

Coarseness: It is a textual analysis and roughness measurement of an image. The texture is seen as being coarser than the one with a higher number and fewer textual qualities. The layer becomes coarser the rougher it is.

$$H = \frac{1}{2^{n+m}}\sum_{y=0}^{n-1}\sum_{x=0}^{m-1} f(y,x)$$

Mean Square Error: One image is assumed to be impure when MSE is measured, whereas the other is assumed to have undergone some form of distortion or manipulation and is referred to be original.

$$MSE = \frac{1}{N\times M}\sum\sum (f(y,x) - f^T(y|x))^2$$

Peak Signal to Noise Ratio: It is a calculation used for the evaluation of the accuracy of the image reconstruction.

$$PSBR \text{ in } db = 20\log\frac{2^{m-1}}{\text{MSE}}$$

D. Classification and Tumor Detection

Convolutional neural networks algorithm is used for classification of brain images. It produces the best results for the image. Brain tumors are automatically categorized into various categories based on their characteristics using machine learning or deep learning techniques in the classification phase of brain tumor detection. Finally, analyze the image using filters and convolutional neural networks algorithm to detect the tumor or non-tumor.

5. Future Works

Currently, the model provides 98% accuracy. Obtaining an excellent data set with high-resolution images obtained directly from the MRI scanner will result in significantly higher accuracy. In addition, classifier boosting methods can be used to further increase the accuracy and get to the point where this tool can be a huge help to any medical facility dealing with brain tumors. There are several potential future works for brain tumor classification, including Incorporating multimodal imaging, which combines multiple imaging techniques such as MRI, CT, PET, and SPECT, can provide more comprehensive information about the tumor and its characteristics, which can lead to more accurate classification. Deep learning algorithms such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have shown promise in accurately classifying brain tumors. Future work may focus on further development and optimization of these approaches. Integrating clinical data such as incorporating clinical data such as patient history, symptoms, and other medical conditions into brain tumor classification can help identify patterns and correlations that can aid in accurate classification.

Fig. 3. Classification error of the model

Table 1

S.No.	Authors	Approach	Percentage
1	Khawaldeh, Saed	Images were applied at the image level rather than at the pixel level	91.16 %
2	Sajjad, Muhammad et al.	Transferee learning and a pre-trained VGG-19 CNN architecture	90.67 %
3	Seetha.J and S.S. Raja	Fuzzy C-Means	97.5 %
4	Rasel Ahmmed, Anirban Sen Swakshar, Md. Foisal Hossain and Md. Abdur Rafiq	Steps such as image preprocessing, segmentation, feature extraction, SVM classification, and tumor stage classification using artificial neural networks	97.44 %
5	Ari, A., & Hanbay, D.	Weighted cranial MR images	96.2

6. Conclusion

In this study, we develop a novel convolutional neural network (CNN) architecture for automatic grading (classification) of brain tumors in three brain datasets including regions of interest, uncropped, cropped, and segmented (ROI). The accuracy of the automated method is comparable to the variability and manual segmentation between observers. Localization of tumors by combining information about unique image structural hierarchies and statistical classifications. The outlined tumor regions are spatially compact, consistent with image content, and provide a reliable and acceptable roadmap for subsequent segmentation. The results of the proposed approach are encouraging. We combine tumor segmentation with semi-supervised learning techniques using a local and global accuracy system, as demonstrated in multiparametric magnetic resonance imaging. Our experimental results show that the proposed approach helps to accurately and quickly identify the exact location of brain tumors.

The experimental findings demonstrated the suggested technology's 98% accuracy in identifying diseased and normal tissues in magnetic resonance imaging.

Segmentation accuracy is affected by tumor size, and errors close to tumor borders are common. A significant fraction of the image pixels that are incorrectly identified are characteristic of large brain tumors. In addition, large tumors can invade the brain and CSF, so defining tumor boundaries can be difficult. It is designed to perform volumetric MRI with different characteristics, including position relative to the overall executive processing time. These features make the entire partitioning process time-consuming. As a result, the processing time of the proposed system was finally determined. Compared to other currently used methods, the proposed method has less classification errors.

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