A ADVANCED JOURNAL IN ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TRENDS IN BIOLOGICAL SCIENCES
Open Journal

Review

The Use of Deep Learning for Brain Tumor Classification: A Study of Cropped, Uncropped and Segmented Lesion Images of Varying Size

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Article information
Received: March 2nd, 2022; **Revised:** June 16th, 2022; **Accepted:** July 21st, 2022; **Published:** August 9th, 2022

Cite this article
Alqudah AM, Alquraan H, Qasmieh IA, Alqudah A, Al-Sharu W. The use of deep learning for brain tumor classification: A study of cropped, uncropped and segmented lesion images of varying sizes. 2022; 1(1). doi: https://doi.org/10.70705/ppp.bioai.2022.v01.i01.pp4-8

ABSTRACT

Deep Learning has recently attracted a lot of interest from academics as the most cutting-edge trend in the machine learning area. Deep learning has shown to be an effective machine learning method, and it has found several uses in tackling complicated issues that call for a high level of sensitivity and precision, such as those in the medical industry. One of the most prevalent and deadly malignant tumor disorders, brain tumors often have an extremely low life expectancy when detected at advanced stages. Thus, following tumor detection, grading is an essential step in developing an efficient treatment strategy for brain tumors. The authors of this study graded 3064 T1 weighted contrast-enhanced brain MR images for tumors into three categories: gliomas, meningiomas, and pituitary tumors. CNN is a popular deep learning architecture that they employed for this task. With an overall performance of 98.93% accuracy and 98.18% sensitivity for the cropped lesions, the proposed CNN classifier is a powerful tool. When applied to uncropped lesions, the results are 99% accuracy and 98.52% sensitivity. When applied to segmented lesion images, the results are 97.62% accuracy and 97.40% sensitivity.

Keywords
Deep learning; Brain tumor; Brain lesions; Cropped lesion; Uncropped lesion; Segmented lesion.

INTRODUCTION

A brain tumor is defined as a tumor affecting the central nervous system, according to the 2016 reclassification of the term by the World Health Organization (WHO). In a nutshell, a brain tumor is just an abnormally growing cluster of brain cells. The brain's neuronal network is severely damaged by these tumors, which in turn affects the brain's function [1, 2, 3, 4]. Tumors in the brain may be either cancerous or non-cancerous, with meningiomas, gliomas, and pituitary tumors being the most common varieties depending on the location of the tumor. The malignancy degree of each of these tumor types is distinct. A pituitary tumor develops on the pituitary gland, gliomas on the glia tissues and spinal cord, meningiomas on the membrane that covers the brain and spinal cord, and pituitary tumors on other areas of the brain [3, 5, 6].

When oncologists first examine a brain tumor, they often use medical imaging procedures like CT scans and Magnetic Resonance Imaging (MRI). Intensely detailed pictures of the brain's anatomy may be generated using these two modalities, and any alterations can be detected. When a doctor has reason to believe a patient has a brain tumor, but wants more confirmation of the tumor's kind, a surgical biopsy is performed to get a more precise diagnosis. Radiologists may now detect even the most minute lesions with greater ease and precision because to advancements in imaging technology that improve picture contrast and resolution specifically for use with brain tissue[7, 8, 9, 10].

By integrating AI with various imaging modalities, computer-aided diagnosis (CAD) systems can be built, which involves combining (fusing) images obtained from various imaging modalities and taking advantage of new engineering technologies that improve the accuracy of brain tumor detection in the field of computer vision. By using these methods, doctors can improve the precision of cancer screenings. Brain tumors have been the target of several AI-based classification and recognition efforts as of late [11–15]. These approaches include convolutional neural networks (CNNs), artificial neural networks (ANNs), and support vector machines (SVMs).

Convolutional neural networks (CNNs) are the cutting edge of machine learning, which is used to diagnose illnesses using medical imaging, especially MRI and CT scans. CNN's ability to train without preprocessing or feature extraction has led to its increased application in medical imaging grading and classification [16, 17]. Typically, convolutional neural networks (CNNs) are used to handle raw pictures with the goal of minimizing or eliminating data pre-processing stages. The following is the sequence in which the many layered layers that make up a CNN: layers of input, convolution, RELU the output layer, the classification layer, and the fully linked layer. The convolution and downsampling processes are the backbone of convolutional neural networks (CNNs) [18, 19]. The convolution uses trainable filters with pre-determined specifications that are fine-tuned during training.

Classifying brain MRI pictures into two broad categories—normal and abnormal—and grading the abnormal images into several forms of brain cancer are the two primary uses of machine learning in brain tumor classification. By drawing attention to itself as a powerful tool in the field of disease detection and classification, CNN has found use in the detection and grading of brain tumors. This, in turn, will improve the accuracy of the detected brain tumor grading, aid doctors in developing an optimal treatment plan, and ultimately increase the healing percentage [20–23].

This study aimed to grade the brain tumor by comparing two scenarios: photographs of the tumor with and without the lesions clipped. These are MRI scans of brain tumors that have been T1-weighted and contrast-enhanced for use in the model. To determine network weights, these pictures are put into a new convolutional neural network (CNN) design during training. Both the cropped and uncropped versions exhibit excellent specificity, sensitivity, and accuracy, according to the findings. What follows is a synopsis of the important findings from this study: A novel convolutional neural network (CNN) architecture has been used in place of pretrained CNNs and transfer learning methods, such as Densenet201. Comparing the model's accuracy using the two sets of images: those with and without lesion segments. Here is how the remainder of the paper is structured: We provide a literature overview of existing approaches to brain tumor grading in Section 2. Section 3 then provides a detailed description of the materials and procedures that were used in this investigation. Section 4 presents the experimental outcomes. Discussion of the findings and, lastly, conclusions on the suggested methods are presented in Sections 5 and 6.

2. LITERATURE REVIEW

Brain tumor identification and grading utilizing various imaging modalities, particularly MRI, has recently seen extensive application of machine learning (ML) and deep learning (DL) approaches. Here you will find the most up-to-date and relevant research papers on the subject of the article. A system that integrates deep learning (DL) methods with features from the discrete wavelet transform (DWT) is proposed by Mohsen, Heba, et al. [8]. Following the utilization of the fuzzy c-mean method for brain tumor segmentation, the features were extracted using DWT for each detected lesion. These features were subsequently input into principal component analysis (PCA) for feature dimension reduction, and finally, the features that were selected were fed into deep neural networks (DNN). Their findings demonstrate a sensitivity level of 97.0% and an accuracy rate of 96.97%. A convolutional neural network (CNN) and features based on a Gray Level Co-occurrence Matrix (GLCM) were introduced by Widhiarso, Wijang, Yohannes Yohannes, and Cendy Prakarsah [10] as a brain tumor classification method. Out of this, four characteristics were retrieved: energy, correlation, contrast, and They used four different datasets (Mg-Gl, Mg-Pt, Gl-Pt, and Mg-Gl-Pt) to test their methodology. The best accuracy achieved was 82.27% for the Gl-Pt dataset using two sets of features: contrast with homogeneity and contrast with correlation. The images were homogeneous from four different angles (0°, 45°, 90°, and 135°). A deep convolutional neural network (CNN) based method for automated brain tumor identification and grading was suggested by Seetha, J., and S. S. Raja [12]. The method utilizes Fuzzy C-Means (FCM) to segment the brain. From these segmented areas, shape and texture data were retrieved and then fed into Support Vector Machine (SVM) and Deep Neural Network (DNN) classifiers. The findings showed that the system had an accuracy rate of 97.5%. However, by using fine ring-form partitioning and area of interest (ROI) augmentation, Cheng, Jun, et al. [13] improved the efficiency of the brain tumor classification method. After making these improvements, they input the feature vectors into a classifier using three distinct feature extraction methods: intensity histogram, GLCM, and bag-of-words (BoW). Based on the results of the experiments, the accuracy increased from 71.39% to 78.18%, 83.54% to 87.54%, and 89.72% to.... has an intensity histogram of 91.28%, a GLCM of 91.25%, and a BoW of 91.28%. In order to reduce the feature dimension of a collection of wavelet features, Sasikala, M., and N. Kumaravel. [17] suggested a genetic algorithm feature selection. Choosing the best features vector to feed into a chosen classifier, such an ANN, is the foundation of the approach. Using only four out of twenty-nine characteristics, the genetic algorithm was able to get a 98% success rate, according to the data. Using a tweaked version of AlexNet CNN, Khawaldeh, Saed, et al. [23] suggested a method for non-invasively classifying glioma brain tumors. We used whole-brain MRI pictures for the classification procedure, and instead of labeling each individual pixel, we did it at the image level. The testing findings demonstrated that the approach attained a respectable 91.16% accuracy, indicating a good performance. A CNN-fused comprehensive data augmentation approach for brain tumor classification was suggested by Sajjad, Muhammad et al. [24]. A technique for classifying brain tumors into many grades utilizing magnetic resonance imaging (MRI) pictures of segmented tumors. Using transferee learning and a pretrained VGG-19 CNN architecture, they were able to obtain an overall accuracy of 87.38% for pre-augmentation data and 90.67% for post-augmentation data. While Özyurt, Fatih et al.

[25] For brain tumor classification, use a CNN in conjunction with NS-CNN sure entropy, which stands for neutrosophic expert maximum fuzzy. To segment brain tumors, they utilized the neutrosophic set - expert maximum fuzzy-sure approach. Next, they submitted the pictures to CNN to extract features, and then to SVM classifiers to determine whether the tumors were benign or malignant. Their average success rate was 95.62 percent.

3. MATERIAL AND METHODS

The main aim and motivation behind this research paper are to provide a new CNN architecture for grading (classifying) brain tumors using T1-weighted contrast-enhanced brain MR images. Figure 1 Shows the Block diagram of the proposed methodology. In this section, the following sub-sections are discussed in detail; the used dataset, and the proposed methodology.

3.1 Dataset

In this paper, we used the brain tumor dataset proposed by Cheng, Jun, et al. [13] which is available online for free at https://figshare.com/articles/brain_tumor_dataset/1512427/5. The dataset contains a 3064 T1 weighted and contrast-enhanced brain MRI's images and includes three classes glioma, meningioma, and pituitary tumor. Table.1 lists the number of images of each class in the dataset. about each image in the dataset is fully described and a full information is provided; such as the patient id (PID), tumor mask, tumor border, and the class label, where the most important information after the class label is the lesion mask which is used to crop the tumor region of interest (ROI). Figure 2 shows a sample of cropped and uncropped lesions images from the used dataset.

CNN is basically based on two processes; convolution using a trainable filter which has a pre-specified size, and weights that adjusted during the downsampling process in the training phase to achieve a high accuracy [10, 26]. In this research, the cropped and uncropped brain tumors images are stored as a database and three folders are created, each one consists of the images for specific class glioma, meningioma, and pituitary tumor. The database is partitioned into training and testing data, where 70% of the data is utilized in the training stage and the rest is used in the test stage. A new CNN architecture is employed in this paper. The next sections will explain the structure of the proposed CNN architecture.

3.2.2 Proposed CNN Architecture

In this paper, we have proposed and used a newly designed CNN architecture. The architecture consists of 18 layers to enable the classifier to grade the brain tumor effectively. This architecture was firstly provided by Alqudah [27] for OCT images classification. In this paper the architecture is modified and transferred to be applied on three different images dataset; cropped, uncropped, and segmented and the performance of the architecture was evaluated. Figure 3 illustrates the structure of the used CNN architecture.

3.2.3 Performance Evaluation

To evaluate the performance of the proposed CNN architecture in grading the brain tumor in both cases; cropped and uncropped image, the confusion matrix for all cases (cropped, uncropped, and segmented) were generated, and a comparison between the CNN architecture outputs with its corresponding original image label was carried out based on these generated confusion matrices. In general, using these generated confusion matrices we can calculate the accuracy, sensitivity, precision, and specificity, to measure how precisely the brain tumor being graded [28].

From the generated confusion matrix, four statistical indices are calculated and used to evaluate the performance of the suggested classification system, namely true positive (TP), false positive (FP), false negative (FN), and true negative (TN) [28, 29] as follows: and testing with a percentage of 70%, 15%, and 15% respectively. The following sections report the results of the proposed two image datasets using the designed CNN architecture. Figure 4 shows the accuracy variation overtraining and validation process during the CNN training process.

4.1 Results of Uncropped Lesion Images

The overall confusion matrices are shown in Figure 5. Based on these figures, we can note that the proposed system has efficiently graded the brain tumor with an accuracy rate values of 97.4%, 99.0%, and 99.2% for input images size of 128x128, 64x64, and 32x32 respectively.

4.2 Results of Cropped Lesion Images

The overall confusion matrices are shown in Figure 6. Based on these figures, we can note that the proposed system has successfully and efficiently had efficiently graded the brain tumor with accuracy rate values of 97.4%, 98.4%, and 96.9% for input images size of 128x128, 64x64, and 32x32 respectively.

4.3 Results of Segmented Lesion Images

The overall confusion matrices are shown in Figure 7. Based

4. DISCUSSION

The dataset that has been used in this paper contains three

All experiments were executed using a desktop computer with Intel Core-I7 processor and 16 Gb RAM. Both image dataset cropped and uncropped were run with a minibatch size of 64, ADAM optimizer as optimizing method, and with learning initial rate of 10-3 which results in 1600 iterations. The dataset was divided into three subsets; training, validation, types of brain tumors; Glioma, Meningioma and Pituitary tumors. In this work, an efficient automatic brain tumor classification is performed by using the proposed convolution neural network. Various manners have been applied to the dataset, such as segmented, cropped and uncropped tumors.

Overall performance evaluation Accuracy as 98.40, Specificity as 99.19 %, Sensitivity as 98.18% and Precision as 98.19%. While segmented images give the lowest overall performance evaluation Accuracy as 97.62%, Specificity as 98.78 %, Sensitivity as 97.40% and Precision as 97.43%. As aforementioned, the uncropped images give the highest results when compared with cropped and segmented lesions. This comes from the cropping process which may discard some pixels around the lesion, which causes low discrimination to the type of the tumor when the results compared with the uncropped cases, which used all pixels and no discarding to anyone [30]. As shown in the presented results, the segmented cases give the lowest results, that is due to the texture color could be used for describing the lesion [31]. Typical color images composed of the three-color channels (RGB) red, green, and blue. In the segmented scheme we used the black color of the binary mask that surrounds the lesion, which is irrelevant to lesion color that is being classified, which leads to counting black in every image even it's not though presented in the lesion [32, 33]. For that reason, the efficiency of the proposed CNN in the segmented lesion is the lowest.

5. CONCLUSION

In this paper, we have presented a new convolutional neural network (CNN) architecture for automated grading (classification) of a brain tumor in three brain datasets; uncropped, cropped, and segmented region of interest (ROI). Our architecture succeeded in grading the brain tumor three classes with high performance in accuracy and sensitivity in all dataset cases; uncropped, cropped, and segmented. The system can significantly grade the tumor into three levels; meningioma, glioma, and pituitary tumor using T1 weight contrast-enhanced brain MR images. This architecture grading efficiency may even be further improved by including more brain MR images with different weights and with various contrast enhancement techniques to allow the architecture to be potentially more generalized and robust application for larger image databases.

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