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Automatic Brain Tumor Detection in Brain MRI Images using Deep Learning Methods

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Abstract

Due to the increased mortality caused by brain tumors, accurate and fast diagnosis of brain tumors is necessary to implement the treatment of this disease. In this research, brain tumor classification performed using a network based on ResNet architecture in MRI images. MRI images that available in the cancer image archive database included 159 patients. First, two filters called median and Gaussian filters were used to improve the quality of the images. An edge detection operator is also used to identify the edges of the image. Second, the proposed network was first trained with the original images of the database, then with Gaussian filtered and Median filtered images. Finally, accuracy, specificity and sensitivity criteria have been used to evaluate the results. Proposed method in this study was lead to 87.21%, 90.35%, and 93.86% accuracy for original, Gaussian filtered, and Median filtered images. Also the sensitivity and specificity was calculated 82.3% and 84.3% for the original images, respectively. Sensitivity for Gaussian and Median filtered images was calculated 90.8% and 91.57%, respectively, and specificity was calculated 93.01% and 93.36%, respectively. As a conclusion, image processing approaches in preprocessing stage should be investigated to improve the performance of deep learning networks.

1. Introduction

Old or damaged normal cells are destroyed and replaced by new cells. Sometimes, this process performs wrongly, and new cells are made and old or damaged cells are not destroyed, which lead to tumor [1]. the American Cancer Society mentioned about 83,570 people in the United States were diagnosed with brain tumors and 18,600 of them died, based on statistical reports published in 2021 [2]. This disease has increased in children due to the development of technology and the use of mobile phones, tablets, etc [3].

Heretofore, 120 types of tumors have been identified, each of which appears with different tissue and sizes that made difficult to identify these tumors in the brain structure [4]. Early detection of brain tumors helps radiologists to improve the diagnosis process and decrease death for this disease. Therefore, due to the increased mortality caused by brain tumors, accurate and fast diagnosis of brain tumors is necessary to implement the treatment of this disease. The choice of treatment method depends on the tumor stage at the time of diagnosis, pathological type, and tumor grade. Computer-Aided Diagnosis (CAD) techniques have helped practitioners in several ways. Applications of CAD in neuro-oncology include tumor diagnosis, classification, and grading. Many researches have been done in the field of brain tumor classification based on CAD into benign and malignant tumors [5]. Grading Glioma, which is a class of malignant tumors, is another research problem in this field [6]. The CAD systems rely on brain MRI images, because MRI image have higher contrast in the soft tissues of the brain compared to

CT images. Recently, studies in the field of CAD have led to better performance due to the emergence of deep learning concepts. Deep learning is widely used in medical studies, from pre-treatment to post-treatment clinical evaluations such as breast cancer, [7], lung cancer diagnosis [8], Seizure detection [9], brain-to-brain communications and synchronization of EEG signals [10], and Brain-Computer Interfaces (BCI) [11] studies. In a study, Zhu et, al. [12] developed an algorithm using deep learning methods to detect tumors in human skin. The monitoring of brain metastases using a deep convolutional neural network (CNN) was investigated in the study of Charon et, al. [13]. In the recent years, transfer learning has made significant progress in object classification and recognition studies [14]. Transfer learning takes a pre-trained model and develops it in another related application. A pre-trained InceptionV3 model to classify benign and malignant kidney tumors in CT images was presented in the study of Zhu et, al. [15]. Deniz et, al. [16] proposed a classification for breast cancer based on histopathological images. Hussein et, al. [17] presented a knowledge transfer based learning model for lung tumor characterization.

According to the brain tumor classification studies, there are important challenges in this field. Related challenges include the following: 1) Brain tumors include many appearances, sizes, and diversity [18]. 2) Tumors may have a similar appearance according to their pathological type [19].

Glioma, Meningioma, and Pituitary tumor are among the most common tumors in the human brain [20]. Cheng et, al. [21] performed 3-class classification on MRI brain images, which was the first classification study to use the challenging Figshare dataset. In this study, the authors extracted many features, and tested a set of classification models. The support vector machine (SVM) gave the best performance in classifying brain tumors. These experiments followed a standard five-fold cross-validation procedure. The performance criteria used were specificity, sensitivity and classification accuracy. Lu et, al. [22] performed a study to classify brain tumors in MRI images. In this study, the dataset of T2-weighted MRI images was used, which included 177 pathological samples and 28 normal samples. ResNet network was used for network training and automatic brain tumor classification. In this network, 14 pathological samples and 14 normal samples were used for testing the network, and the rest for training the network. The performance of the proposed network represents a better trend compared to previous studies in the automatic classification of brain tumors. Liu et, al. [23] evaluated the capability of ResNet34 architecture for brain tumor classification. They used an algorithm called G-ResNet for classification, which was based on the architecture of ResNet, which instead of the flat layer, a maximum overall integration layer was used. Finally, the features were combined with high and low-level features. The results of this study showed that the proposed new G-ResNet network achieved high accuracy with optimal loss performance.

Although the problem of classification and automatic detection is the main problem in this research work, but according to previous studies, it should be noted that the problem of pre-processing is very effective in more accurate detection and reducing the learning time of the network. This issue has been considered in many studies. For example, in the study of Gholizadeh-Ansari et, al. [24], an edge detection layer was used to improve the quality of chest CT scan images of patients with covid-19. By adding this edge detection layer, the processed images had better quality [25]. On the other hand, removing the noise of the images in the pre-processed stage is of particular importance. Especially when brain imaging is done using a CT scan machine, the quality of the images decreases with a decrease in the radiation dose or the presence of a rectifier. In Hiltz et, al.'s [23] study, they used several filters such as smoothing and averaging filters to reduce noise and improve the quality of CT scan images. The results of this study showed that the median filters preserve the edges better than the averaging filters [26].

In this paper, we developed an automatic classification system designed for Glioma diagnosis in MRI imaging. This implementation uses a deep learning model based on ResNet architecture in brain MRI image classification. The improved image quality is performed by the Median and Gaussian filters. In addition, the canny operator is presented for tumor edge detection in pre-processing section. Finally, 3 datasets (original image, Gaussian, and Median-filtered image) are considered as input of the proposed network.

The remainder of this article is organized as what follows. In Section 2, we describe the method performed, which is followed by a description of the datasets used in the study and the complete framework for the proposed classification algorithm. Section 3 mentions the results. Finally, Sections 4 and 5 are presented for discussion and conclusion, respectively.

2. Materials and Method

MRI images are such efficient in diagnosing brain tumors because of the high contrast between soft and hard tissue.

2.1. Data acquisition

The accuracy of brain tumor classification depend on rich database for CAD analysis based on deep learning methods. In this study, the images available in the cancer image archive database were used [27]. This dataset includes 159 MRI image patients (83 men and 76 women) with low-grade glioma in three T_1-weighted (T_1W), T_2-weighted (T_2W), and FLAIR imaging sequences. Table 1 shows the general characteristics of patient and device information. All images were segmented by two experienced radiologists into three parts including brain tissue, non-increasing tumor, and increasing tumor. Images with non-increasing and increasing tumors were labeled as zero and one, respectively.

Table 1. Device and patient's characteristics.

Patient and device	Measure
Number of patients	159
Age	56 ± 22 (years)
Device	Ingenia 1/5 T (Philips)
Type	FLAIR
Size	512 × 512

2.2. Pre-processing

Image processing is one of the important issues in engineering sciences, especially medical engineering. Since there are various imaging devices such as CT scan, Magnetic Resonance Imaging, Ultrasound Imaging (UI), Positron Emission Tomography (PET), etc. [28, 29], in the medical imaging department, it shows the importance of using image processing techniques in image quality improvement.

2. 2. 1. Gaussian filter

Gaussian filter is a simple and intuitive approach of noise suppression that replaces the value of each pixel with the weighted average of surrounding ones. This approach may introduce noticeable signal loss and blurring in the MRI images [30]. The Gaussian filter is defined as:

$$F(x,y)=\frac{1}{2\pi\sigma^2}e^{\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

where, x and y are the vertical and horizontal distances from the target pixel (in two-dimensional implementation), and σ is the standard deviation of the Gaussian distribution. The kernel obtained from this equation is convolved with the noisy MRI images to diminish the noise levels. The standard deviation of the Gaussian kernel is the key parameter that defines the levels of smoothness in the resulting images.

2. 2. 2. Median filter

The Median filter, as a non-linear denoising approach, is commonly used for noise suppression in natural as well as medical images. The Median filter is functionally similar to the moving average filter, but it calculates the median value of the pixels/voxels rather than the mean value. Median filters might exhibit better performance regarding the edge preservation in the filtered images compared to the Gaussian filter [31]. The median filter is formulated as:

$$F(x,y)=median(g(x,y)) \quad (2)$$

where x × y defines the size of the filter window for calculation of the median value.

2. 2. 2. Canny operator

An edge detection operator canny uses a multi-step algorithm to detect a wide variety of edges in images. Edge detection is a technique for extracting useful structural information from various objects and dramatically reducing the amount of data to be processed, which has been widely used in machine vision systems. An edge detection solution can be implemented in a wide variety of situations.

The optimal function in the Canny detector is described by the sum of four exponential terms, but it can be approximated by the first Gaussian derivative. Among the developed edge detection methods, the Canny edge detector algorithm is one of the most accurate methods that provide powerful and reliable detection [32].

The process of edge detection algorithm can be divided into four different steps:

1- Finding image intensity gradients.

2- To avoid a false positive response in edge detection, the gradient magnitude threshold or lower bound cut inhibition is used.

3- Double thresholding is used to determine the potential edges.

4- Edge detection is finalized by suppressing all other edges that are not connected to strong edges.

The Canny edge detection algorithm was applied after improving the quality of the images. This approach helps to highlight tumor edges in images and improve the performance of the proposed network.

2.3. Classification

ResNet, short for Residual Network, is a specific type of neural network that was introduced in 2015 by [33]. Mostly, in order to solve a complex problem, we stack some additional layers in the Deep Neural Networks, which results in improved accuracy and performance. The intuition behind adding more layers is that these layers progressively learn more complex features. We notice to be different is that there is a direct connection, which skips some layers in between. This connection is called 'skip connection' and is the core of residual blocks. Due to this skip connection, the output of the layer is not the same now. Without using this skip connection, the input 'x' gets multiplied by the weights of the layer followed by adding a bias term. The skip connections in ResNet solve the problem of vanishing gradient in deep neural networks by allowing this alternate shortcut path for the gradient to flow through. The ResNet architecture has been used for several applications for instance image classification, segmentation, and object detection [34]. In this study, automatic tumor classification in brain MRI images was performed by ResNet architecture. 9 ResNet architecture blocks were placed sequentially and the layers of each block of the proposed network are shown in Figure 1. This figure represents the structure of the ResNet idea, which uses convolutional layers in each block. Each block of this structure includes two convolutional weighted layers and one identity layer, which this layer is usually not considered in the calculation of the number of layers. Also, at the beginning of the proposed network, there is a convolutional layer with 16 filters, and at the end of the proposed network, there is a dense layer with a sigmoid activation function. The proposed network is shown in Figure 2.

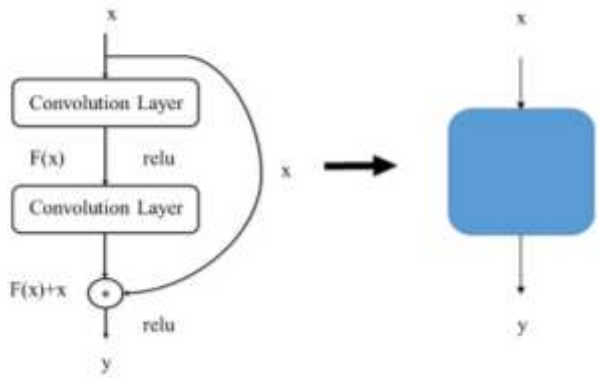


Figure 1. ResNet architecture structure and corresponding block.

Figure 2. Proposed method for brain tumor classification.

Overall, the proposed network includes 13 blocks based on Figure 2, in which binary cross entropy is used for the loss function and Adam's optimizer in order to train the network. In this study, 120 patient images were used for training and 30 images for testing the network. Proposed Network performed in a processing system based on Table 2.

In total, the network is trained 3 times by original images, Gaussian-filtered images, and Median-filtered images on which the edge detection process had been performed. K-fold cross-validation was used to validate the results from the network on the dataset. In this study, the data was divided into k = 5 subsets, and each time 120 patient images were considered for training and 30 patient images for testing the network.

Table 2. Proposed method for brain tumor classification.

System	Parameters
CPU	Intel Core i5
GPU	Invidia RTX 3050Ti
RAM	16 (G)
Library Package	Keras

Finally, the average of 5-fold cross-validation results is considered as the result. Table 3 summarizes network information.

Table 3. Overall setting Information of proposed network.

Network information	Number
Training images	100
Validation images	30
Testing images	29
Batch size	5
Epoch	100
Convolution layers	23
Dense layers	1
Flatten layers	1
Kernel size	16

2.4. Quantitative evaluation
There are different features to evaluate the efficiency of algorithms. Comparing the performance are dependent on the quantitative evaluations. Accuracy, sensitivity, and specificity are using for different pre-processing situation.

2.4.1. Accuracy
The accuracy proposed network classification was calculated for each training dataset. The closer the accuracy is to 100%, the better the classification of tumor images. To calculate the accuracy, some definitions must be stated:

A. True Positives (TP): images that are correctly recognized by the network as tumors.

B. False Positive (FP): images that are wrongly detected by the network as images with a tumor.

C. True Negatives (TN): images that are correctly recognized by the network as images without tumors.

D. False Negatives (FN): images that are wrongly detected by the network as images without tumors.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

2.4.2. Sensitivity
An important indicator in the statistical evaluation of classification performance is the results of binary classification tests. After analysis, the results can be divided into positive and negative groups. In fact, the quality of the algorithm can be measured using sensitivity criteria. Calculation of the sensitivity can be expressed according to the following relationship:

$$Accuracy = \frac{TP}{TP + TN} \quad (4)$$

2.4.3. Specificity
The ability of the network to find tumor-free images is called specificity. To calculate the network specificity, the ratio of true negative images to the sum of true negatives and false positives must be obtained. Mathematically, this ratio can be expressed as the following relationship:

$$Accuracy = \frac{TN}{FP + TN} \quad (5)$$

3. Results
Figure 3 shows the original images, Gaussian-filtered images, and Median-filtered images. Region of Interest (ROI) that include brain tumor are zoomed in images. Performed the Gaussian filter, the image is slightly blurred, which is normal due to the average nature of the Gaussian filter. Performed the median filter can be shown that the edge of image has been preserved better.

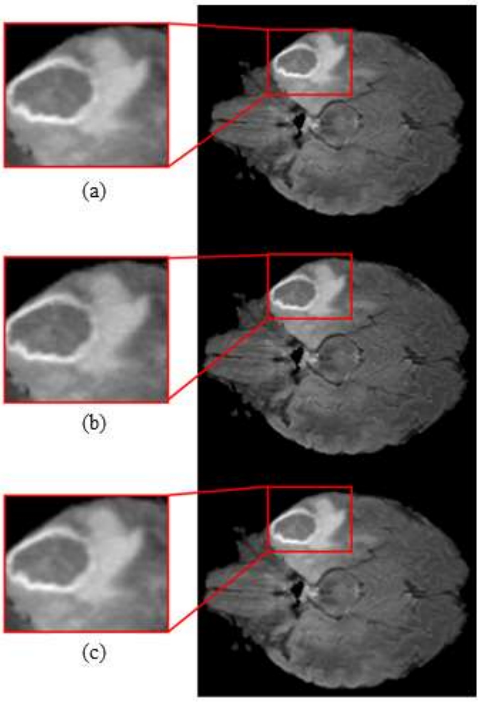
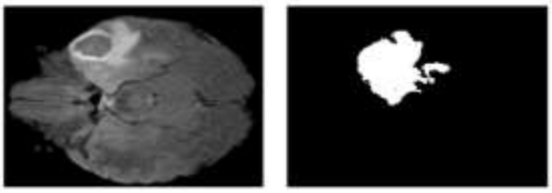


Figure 3. Brain tumor in axial FLAIR image. a) Original image, b) Median-filtered image, and c) Gaussian-filtered image.

As mentioned, these databases have segmentation features, which have performed by two radiologists. Figure 4 (a) shows an example of a segmented tumor in an MRI image. By applying edge detection, Figure 4(b) is obtained, where the edges of the image are detected. Then, these edges are added to the Gaussian-filtered images and Median filtered images. Figure 5 shows examples of images obtained after applying the canny edge detector.



(a) (b)

Figure 4. a) Brain tumor image and b) Tumor segmented existed on dataset.

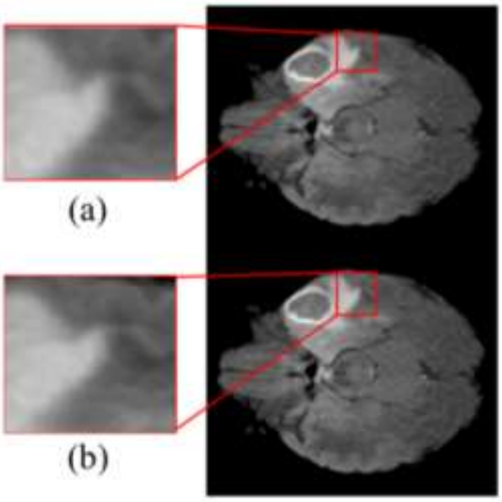


Figure 5. Adding tumor edges to a) Gaussian-filtered image and b) Median-filtered image.

After performing the pre-processing step, the images were ready to enter the proposed network for classification. In the previous section, detailed explanations have described the network and its settings.

Figure 6 shows the diagrams related to the implementation of the proposed network (the diagram related to the input of original images, Gaussian filtered images, and Median filtered images in the proposed network). In this Figure, the orange graphs show the training accuracy and the blue graphs show the test accuracy. The graphs show that improving the quality by using the median filter improves the learning process of the network (Figure 4 (c)). In median filtered images, as the number of epochs increases, the accuracy changes are less than other situations.

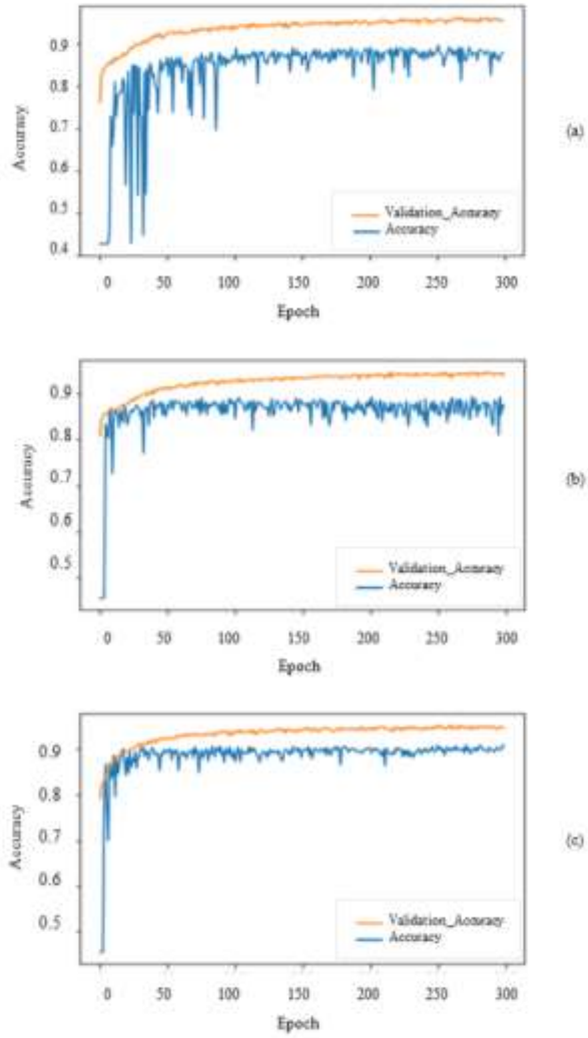


Figure 6. Training and validation accuracy for a) original image, b) Gaussian-filtered images, and c) Median-filtered images.

Table 4 shows the comparison of the accuracies calculated from the mentioned methods. This improvement in the accuracy of the calculated results shows the importance of the pre-processing process that was considered in this study. Also, the sensitivity and specificity for the original images were calculated 82.36% and 84.53%, respectively, while for Gaussian-filtered images, the sensitivity and specificity were calculated 90.85% and 91.57%, respectively, and for Median-filtered images were calculated 93.01% and 93.36%. Table 4 shows the details of the obtained results. The summary of the obtained results is shown in Figure 7.

The calculated results show the better performance of the network in using inputs with reduced noise by Median filter, which was expected cause the better preservation of edges in images.

Table 4. Accuracy, sensitivity, and specificity results for original, Gaussian-filtered, and Median-filtered images classification.

Input images	Orginal brain tumor images classification	Gaussian filtered brain tumor images classification	Median filtered brain tumor images classification
Accuracy	87.21	90.35	93.86
Sensitivity	82.36	90.85	93.01
Specificity	84.53	91.57	93.36

4. Discussion

MRI images are suitable candidates for brain imaging because of the good contrast between soft and hard tissue. As the tumor grows, the sensitivity of MRI imaging increases. Early tumor diagnosis is difficult due to the tumor tissue in the early stages and its size. For this reason, computer-based approaches can help specialists in this field. As mentioned, brain tumor diagnosis is one of the most important studies that have been investigated recently. Excellent performance of deep learning methods leading to automatic brain tumor classification has been an interesting research field in the last few studies. This study was conducted with the aim of classifying images with tumors and without tumors. The accuracy of applying the network to the original images was 87.21%. However, the accuracy calculated by applying the network to the Gaussian-filtered and Median-filtered images was 90.35% and 93.86%, respectively.

The classification training time for Gaussian and Median filtered image patients was less (13 seconds) than training proposed network with original images. This means that by considering the pre-processing issues, not only the classification accuracy can be increased, but also the processing time can be reduced.

Edge detection can be cause of reduction time in implementation of processing. On the other hand, highlighting the edges of the image and reducing its noise can change the occupied space of the processing system. For this reason, changing the size of the stored images after pre-processing, compared to the original images, can be effective in reducing the network execution time. Although the reduction of the processing time mainly occurs in the changes related to the network, however, the execution of the network with different pre-processing can change the execution time of the network.

Singh et, al., classified three distinct forms of brain tumors. A convolutional neural network architecture proposed for their purpose, and 92.50% was the best accuracy rating [35]. However, pre-processing approaches were not investigated in this study. According to Table 4, denoising and edge detection methods discussed in our study can be improvement accuracy in this study. G-ResNet network that introduced in Liu et, al. was a developed ResNet Network[23]. However, pre-processing approach was not considered in this study. Therefore, the pre-processing methods investigated in this study can lead to a better performance of Liu et, al.'s study. Saxena et, al. (2020) implemented VGG-16 and Inception-V3 model for brain tumor classification and calculated accuracy of 90% and 55%, respectively [36]. Image pre-processing approach can improve their results based on proposed method in this study. Gumaei et, al. (2019) improved brain tumor classification accuracy by 3%, while the proposed method has a 6% increase in the highest accuracy [37].

Although this study achieved high accuracy in the automatic brain tumor classification process, it should be noted that other brain tumors such as astrocytoma and ependymoma were not considered. Also, the number of available images in the used database is limited, and future studies should consider richer databases.

This study suggested that in future studies will combine other pre-processing methods. Different noise removal and edge detection operators can be used together to investigate execution time of the network.

Therefore, this study examines the established part state-of-the-art in more detail, and shows that pre-processing can be an important factor in the results obtained from the implementation of deep learning network.

5. Conclusion

As mentioned, the best accuracy related to network training was with Median filtered images, which was calculated 93.86%. Also, sensitivity and specificity results were calculated better compared to other network input images. Although this study achieved high accuracy in the automatic brain tumor classification process, however, noted that other brain tumors such as astrocytoma and ependymoma were not considered according to the selected database. Also, the number of images in the used database is limited, and future studies should consider richer databases. Due to the increasing development of artificial intelligence and deep learning algorithms, we predict that the algorithms in this field will move towards achieving higher accuracy in diagnosis, the possibility of classifying tumors according to their grade, and segmenting them simultaneously. Network execution time can be changed with different pre-processing methods, and research is needed in this field to more accurately examine the effect of preprocessing on network execution time. Also, the development of more databases in this field is one of the other interesting study topics that will solve the need to generate data in the training of deep learning algorithms. This research work suggests that the proposed network be compared with other brain tumor classification networks.

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آشکارسازی اتوماتیک تومورهای مغزی در تصاویر ام آر آی با استفاده از یادگیری عمیق

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چکیده:

با توجه به افزایش مرگ و میر ناشی از تومورهای مغزی، تشخیص دقیق و سریع تومورهای مغزی برای درمان این بیماری ضروری به نظر می‌رسد. در این پژوهش، طبقه‌بندی تومور مغزی با استفاده از شبکه مبتنی بر معماری ResNet در تصاویر MRI انجام شد. تصاویر MRI موجود در پایگاه داده آرشیو تصاویر سرطان شامل ۱۵۹ بیمار بود. ابتدا برای بهبود کیفیت تصاویر از دو فیلتر میانه و گاوسی استفاده شد. عملگر تشخیص لبه به نام کَنی نیز برای شناسایی لبه‌های تصویر استفاده شد. در مرحله دوم، شبکه پیشنهادی ابتدا با تصاویر اصلی پایگاه داده، سپس با تصاویر فیلتر شده گاوسی و فیلتر شده میانه آموزش داده شد. در نهایت برای ارزیابی نتایج از معیارهای دقت، تشخیص پذیری و حساسیت استفاده شده است. روش پیشنهادی در این مطالعه منجر به دقت ۸۷/۲۱٪، ۹۰/۳۵٪ و ۹۳/۸۶٪ به ترتیب برای تصاویر اصلی، فیلتر شده گاوسی و فیلتر شده میانه بود. همچنین حساسیت و تشخیص پذیری نیز برای تصاویر اصلی به ترتیب ۸۲/۳ ٪ و ۸۴/۳ ٪ محاسبه شد. حساسیت برای تصاویر فیلتر شده گاوسی و میانه به ترتیب ۹۰/۸٪ و ۹۱/۵۷ ٪ و تشخیص پذیری به ترتیب ۹۳/۰۱٪ و ۹۳/۳۶٪ محاسبه شد. به عنوان نتیجه گیری، رویکردهای پردازش تصویر در مرحله پیش پردازش به منظور بهبود عملکرد شبکه‌های یادگیری عمیق باید مورد بررسی بیشتری قرار گیرد.

کلمات کلیدی: یادگیری عمیق، پردازش تصویر، تشخیص خودکار، تومور مغزی، ام آر ای.