Brain Tumor Detection Using Magnetic Resonance Images Through Convolutional Neural Networks

Detección de Tumor Cerebral Usando Imágenes de Resonancia Magnética a Través de Redes Neuronales Convolucionales

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Abstract

Nowadays, brain tumor classification is a crucial task for neurologists and radiologists. However, manually detecting brain tumors from magnetic resonance imaging (MRI) can be challenging and prone to errors. This study proposes a method using neural networks to detect brain tumors. This study uses a subset of the BRATS 2018 dataset that contains 1,992 brain MRI scans. The proposed model achieves an accuracy of 97% in the test set making it a tool for medical experts.

Keywords: Image processing, Brain tumor, Deep learning, Convolutional neural networks

Introduction

A brain tumor is a growth of cells in the brain or near it. Brain tumors can appear at any location, in different image intensities, and can have different shapes and sizes (Ayadi, W., Elhamzi, W., Charfi, I. et al. 2021). Brain tumors are divided into two categories, malignant and benign. The main feature of benign brain tumors is that they contain cancer cells. A surgical method can be applied to eliminate the benign tumors. However, malign brain tumors have an irregular shape and contain cancer cells, which makes it dangerous to apply surgical methods (Xie, Y.; Zaccagna, F.; Rundo, L.; Testa, C.; Agati, R.; Lodi, R.; Manners, D.N.; Tonon, C. 2022). Radiotherapy, chemotherapy, or a combination of these can treat this kind of tumor. Therefore, a quick diagnosis plays an important role in further treatments.

In recent years, new methods have been introduced to diagnose malignant brain tumors. These methods are based on statistical features that describe the entire image in a single point. In (Abiwinanda, N., Hanif, M., Hesaputra, S.T., Handayani, A., Mengko, T.R. 2019) a set of texture features based on gray level co-occurrence matrix (GLCM) are extracted from magnetic resonance images (MRI) to classify malignant tumors. In (A. Saleh, R. Sukaik and S. S. Abu-Naser 2020) a genetic algorithm is used to select the most relevant features in MRI images. In (J. Amin, M. Sharif, M. Raza, T. Saba and A. Rehman 2019) statistical features are used to extract relevant information from MRI images. Although the statistical features are achieved to classify malignant brain tumors, a low accuracy is reached to apply these methods. This is due to the statistical features does not extract relevant information from MRI images. For these reasons, models based on convolutional neural networks (CNN) have arisen as an alternative to statistical methods.

In this study, a new CNN topology is used to classify malignant brain tumors. The CNN is formed by 5 blocks of convolutional operations, after that, fully connected layers are used to predict brain tumors. In this work, MRIs are divided into training and testing subsets to validate the neural network. The neural network model reached 97% of classification using this neural network.

Methodology

In this section, the methodology used to classify malignant brain tumors is explained. Figure 1 describes the process used to create a CNN. From this figure, it can be observed that the classification process is divided into three parts: preprocessing, training validation, and testing. In the preprocessing stage, the images are submitted to the rescaling and normalization process. In the training-validation stage, the preprocessing images are divided into two sub-sets used to train and validate the neural network. Finally, in the testing stage, a subset of images is used to validate the neural network.

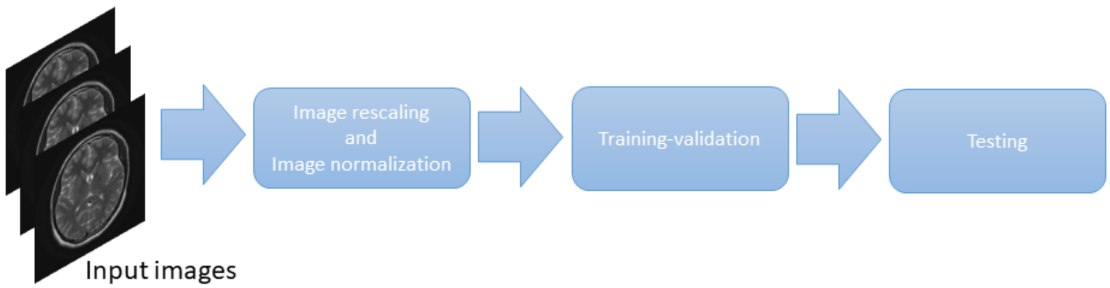

Figure 1. Overall design used to create a brain tumor classifier
Source: Author's own elaboration.

Preprocessing

In deep learning, the image preprocessing is a set of techniques used to prepare the data. The main objective is to create a set of structured data to avoid errors in the training process (Rinesh, S., Maheswari, K., Arthi, B., Sherubha, P., Vijay, A., Sridhar, S., ... & Waji, Y. A. 2022). The most common preprocessing techniques used in image processing are resizing and rescaling (Neelima, G., Chigurukota, D. R., Maram, B., & Girirajan, B. 2022). The resizing technique is used to modify the shape of the image. There are different methods used to resizing an image, in this study, the bilinear interpolation is used to resize an image. The bilinear interpolation calculates by considering a weighted average of the nearest neighboring pixels. Thus, the bilinear interpolation can be calculated according to the equations 1 and 2:

$$f(x, y_1) = \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21}) \tag{1}$$

$$f(x, y_2) = \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}) \tag{2}$$

Where Q_11, Q_21, Q_12, and Q_22 are four known points in the original image. $f(x, y_1)$ and $f(x, y_2)$ is the new pixel in the resizing image. In addition to rescaling images, the rescaling technique is one of the most common preprocessing methods used in image processing. The objective of rescaling is to set a new pixel scale in an image, this method improves the convergence in machine learning models. Figure 2 shows the process used to rescale the image.

$$\begin{bmatrix} 255 & 255 & 255 \\ 155 & 25 & 55 \\ 75 & 18 & 20 \end{bmatrix} \frac{1}{255} = \begin{bmatrix} 1 & 1 & 1 \\ 0.60 & 0.09 & 0.21 \\ 0.29 & 0.07 & 0.07 \end{bmatrix}$$

Figure 2. Process of rescaling image.
Source: Author's own elaboration.

From this figure a factor is multiplied by an image, the result is used as an input in the neural network model.

Convolutional neural network model

In medical image analysis, CNN is a medical tool used to describe the patient's conditions (Ayadi, W., Charfi, I., Elhamzi, W. *et al 2022*). The CNNs are assembled according to a specific shape. This shape allows the extraction of relevant features from the data and can make a task. Figure 3 shows the shape used to classify malignant tumors from MRI.

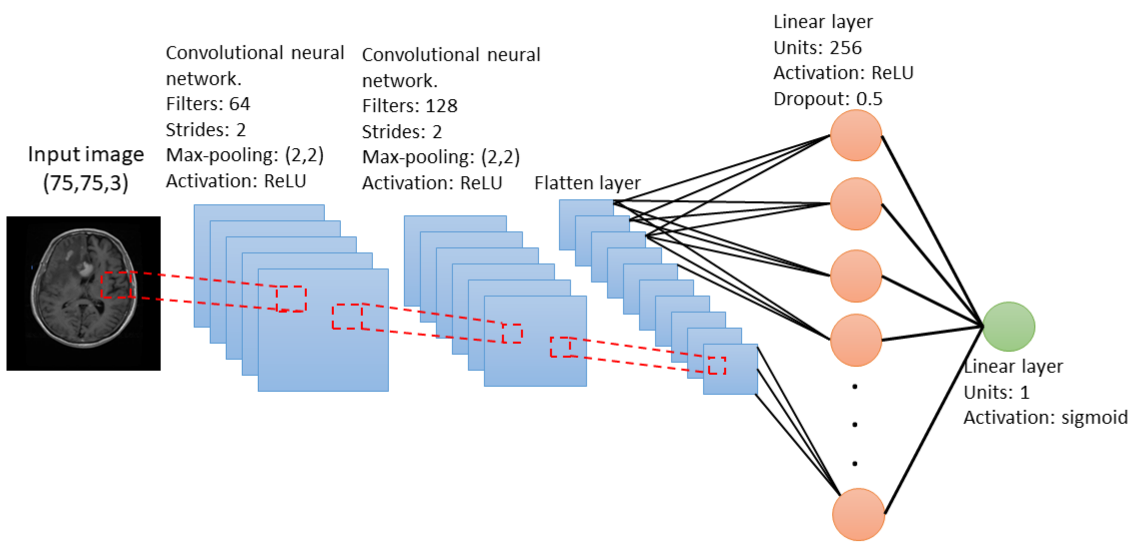

Figure 3. Neural network structure used to classify malignant tumors.
Source: Author's own elaboration.

From this figure, the CNN is formed by two convolutional blocks formed by 64 filters and a ReLU as an activation function. Once the second block is computed, a flattened layer is used to create a vector. This vector passes through a fully connected layer. The fully connected layer is formed by 256 units, ReLU as an activation function and 0.5 dropout. Finally, the last layer is formed by one unit and a sigmoid as an activation function. The final CNN model uses binary cross-entropy loss, stochastic gradient descent like an optimizer, and is trained by 15 epochs.

Results

In this section, the results obtained to train and test the CNN are presented. Firstly, the database used to train the model and the obtained results to train the convolutional neural network are presented. Subsequently, it describes the results of testing, and finally, a comparison with the state-of-the-art models.

Training results

For the training process, the data set is composed of training and testing. The training dataset is formed by 3680 images (1840 images belonging to healthy and the rest to no malignant tumor) where 368 (184 images belong to healthy and the rest to no malignant tumor) images are used to validate the CNN model. The testing set is formed by 920 images where 460 images belong to the healthy class and the rest to malignant tumors. The dataset used in this study is the BRATS 2018. Figure 4 describes the results obtained to train the CNN. From figure 4(a) it can be observed that the maximum accuracy and the minimum loss are reached in the eleventh epoch. The accuracy reached in using this CNN is 97% with a binary cross entropy loss of 0.098.

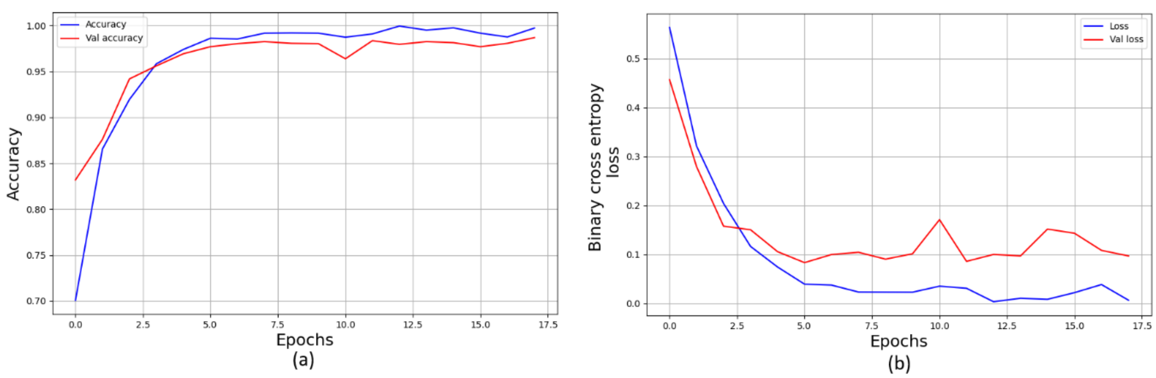

*Figure 4. Obtained results in the training process a) Accuracy results, b) Binary cross entropy loss results.
Source: Author's own elaboration.*

Testing results

The obtained results to test the neural network are presented in Table 1. From this table, it can be observed that the accuracy obtained is 97%. For the healthy class, 447 samples were classified correctly and 13 were misclassified. For malignant tumors, 446 samples were correctly classified and 14 were misclassified.

Table 1. *Classification results in the test set.*

Class	**Healthy**	**Malignant tumor**
Healthy	447	13
Malignant tumor	14	446

Source: Author's own elaboration.

Comparison

We compare the results obtained with different statistical models. Table 2 shows different methods used to classify malignant tumors.

Table 2. *Comparison with different methods.*

Author	Method	Accuracy
Cheng J, Huang W, Cao S, Yang R, Yang W, et al. 2015	Texture	84.5%
Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., & Alassafi, M. 2021	Transfer learning	93.1%
Proposed	Deep learning	97.0%

Source: Author's own elaboration.

From this table, it can be observed that the texture methods do not extract relevant information from MRI images. In the transfer learning approach, although the accuracy obtained is satisfactory, the features extracted from the pre-trained models do not contain discriminatory information to achieve better accuracy.

Conclusion

In this study, a model is proposed to classify malignant tumors from MRI. The CNN is used to extract relevant features from the MRI and is used to infer the patient's condition. The performance of this model was addressed and compared with the existing models in the state-of-the-art. The models based on CNN produce higher accuracy in comparison with statistical approaches. This work could be an important tool for medical analysis. Future works will be based on test image segmentation and classification in MRI.

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