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Edge impulse-based convolutional neural network for brain tumor classification

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Abstract. Brain tumor, a type of intracranial tumor, poses significant threats to human health. In an effort to improve the accuracy and efficiency of tumor recognition and classification, this paper used convolutional neural network to train the model through the Edge Impulse platform. In this paper, BrainChip's Keras-based classification model was selected as the learning block. The initial data set was broken down into training set and test set categories for data processing. Data in the training set made up 88% of the overall data set, whereas data in the test set made up 12% of the total data set. In this paper, the number of training epochs was set as 10. In addition, under the condition that other conditions remain unchanged, this study conducted the experiment with the learning rates of 0.0005, 0.001, 0.002 and 0.003 respectively. After training models with different learning rates through convolutional neural network, four groups of results with different accuracy were obtained in this study. Finally, this study's experiment produced the most accurate results (87.0%) when the learning rate was 0.002. The findings of this study suggest that training a CNN model can effectively and accurately identify different types of brain tumors in a large dataset.

Keywords: convolutional neural network, brain tumor, machine learning.

1. Introduction

The phrase "brain tumor" refers to any intracranial tumor, including both primary brain tumors that develop from the brain parenchyma and secondary brain cancers that spread to the brain from other body organs [1]. These tumors can result in severe damage to the human body, including increased intracranial pressure and compression of brain tissue, leading to pain and damage to the central nervous system [2]. Additionally, they can result in severe disabilities like seizures, issues with speech or memory, and physical dysfunction [3]. The incidence of brain tumor-related deaths in China was recorded at16,351 in 2016, ranking 10th in the spectrum of cancer deaths [4]. Notably, in 2020, China had the highest number of brain tumor deaths in the world [5]. In this case, the treatment of brain tumor patients is one of the important topics in today's medical field and timely detection of brain tumors is a key prerequisite for effective treatment of patients.

Magnetic resonance imaging (MRI) was previously the most commonly used method for detecting brain tumors. However, its efficacy is limited due to varying assessment methods among professionals, resulting in inconsistent results, and it fails to identify the type of tumor, which is critical for early treatment [6]. The convolutional neural network (CNN) can achieve better performance than manual classification. A type of feedforward neural network with depth structure and convolutional processing is the convolutional neural network [7]. It can immediately feed the network with original data and then perform implicit network learning using training data [7]. This technique uses automatic categorization, avoiding the drawbacks of human feature extraction and mistake accumulation. At present, there have been studies using convolutional neural networks to train models, hoping to classify and recognize brain tumors. For example, Havaei et al. extract both the local and global properties of the image while simultaneously splitting the network training procedure into two steps [8]. This method has made great progress in the segmentation effect, but some patients have low accuracy in some indicators. The reason for this is that the boundary between enhanced and non-enhanced areas is not clear.

In this case, this study trained the convolutional neural network model by the platform of Edge Impulse and conducted the related experiments. In this way, the model trained by this study can effectively classify the data set and obtain the training results with satisfactory accuracy. The data for this article comes from data sets in Kaggle [9]. The study selected the Classification (Keras) - BrainChip Akida™ as the learning block. The study trained the model with the learning rate of 0.0005, 0.001, 0.002 and 0.003 respectively. The learning rate of 0.002, with an accuracy of 87.0%, has the best accuracy among them.

2. Method

2.1. Dataset preparation

The data utilized in this study was obtained from Kaggle and consisted of 3,111 MRI brain images with a pixel size of 96×96 [9]. These images were classified into four categories: pituitary tumor, meningioma tumor, no tumor, and glioma tumor. Additionally, grayscale was used to generate the features of all images. The data were divided into training and testing sets for each category. Specifically, the glioma tumor class contained 913 images, with 822 in the training set and 91 in the test set. The meningioma tumor class contained 933 images, with 819 in the training set and 114 in the test set. The no tumor class contained 368 images, with 285 in the training set and 83 in the test set. Finally, the pituitary tumor class contained 897 images, with 826 in the training set and 71 in the test set. The training set represented 88% of the total dataset, while the test set accounted for 12%. Sample images of the four types of brain diseases in the dataset can be found in Figure 1.

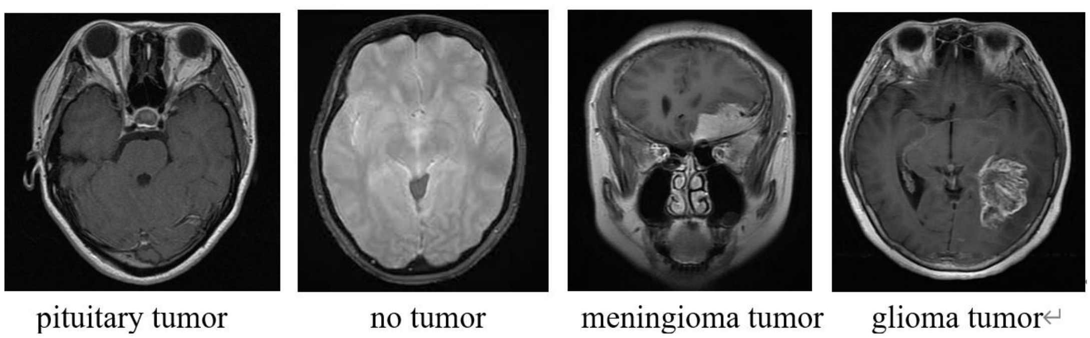

Figure 1. Sample in the collected data set.

2.2. Edge Impulse-based brain tumor classification

Edge Impulse is a cloud-based AI platform that provide assistance in training custom models. The workflow of this platform is structured into three primary stages: information acquisition, data processing and training model. The model can be trained by uploading data to the Edge Impulse platform and designing the impulse.

Convolutional neural network, one of the main deep learning algorithms, is useful in a variety of applications, including object detection and computer vision [7]. Input layer, convolutional layer, pooling layer, full connection layer, and output layer make up the fundamental components of CNN

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[10]. Convolutional layer and pooling layer are two of them that are utilized for information extraction, and information is integrated via a full connection layer [7]. Meanwhile, the use of dropout in the full connection layer can prevent overfitting and enable neuron learning to obtain more robust features [7].

In this study the data was imported into the Edge Impulse platform firstly and in the process of uploading data, it is necessary to seperate the data into training set and test set. The second step is impulse design, which includes three parts: impulse creation (selecting the learning block and the type of output features), feature generation of the pictures in the data set and train the model. Among them, the type of learning block, the way of image processing and the setting of parameters during model training will affect the accuracy of the results.

2.3. Implementation details

In the selection of learning block, the study chooses a classification model based on Keras, which is launched by BrainChip company. As a neuromorphic system-level chip,which is called Akida, it can complete tasks with higher efficiency and lower energy consumption. The type of output results is the same as the classification of data set, which is pituitary tumor, meningioma tumor, no tumor, and glioma tumor. The pertinent model training parameters are established when the grayscale images are created. The CNN selected in this paper is shown in Figure 2, with one input layer, two convolutional layers and pool layers, one flattens layer, one dropout and one output layer.

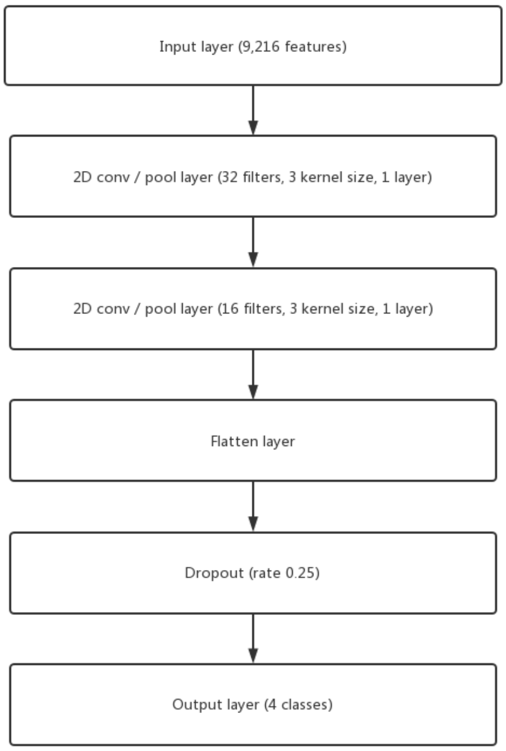

Figure 2. Structure of the CNN.

When the number of training epochs is fixed at 10 and other conditions are held constant, the study trained the model with different learning rates. In this paper, four different learning rates of 0.0005, 0.001, 0.002 and 0.003 are selected for the experiment, and four different experimental results are obtained.

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3. Results and discussion

Based on the above four groups of experiments, the study obtained the corresponding experimental results as shown in Table 1. Analysis of Figure 3 revealed that the learning rate of 0.002 yielded the highest accuracy of 87.0% and the lowest loss of 1.51. Notably, the accuracy rates for pituitary tumor, meningioma tumor, no tumor, and glioma tumor were 97.3%, 80.9%, 81.0%, and 86.7%, respectively.

Table 1. The performance of the model based on different learning rate.

Learning Rate	Number of Training epochs	Accuracy	Loss
0.0005	10	75.1%	4.53
0.001	10	84.3%	2.32
0.002	10	87.0%	1.51
0.003	10	84.9%	2.09

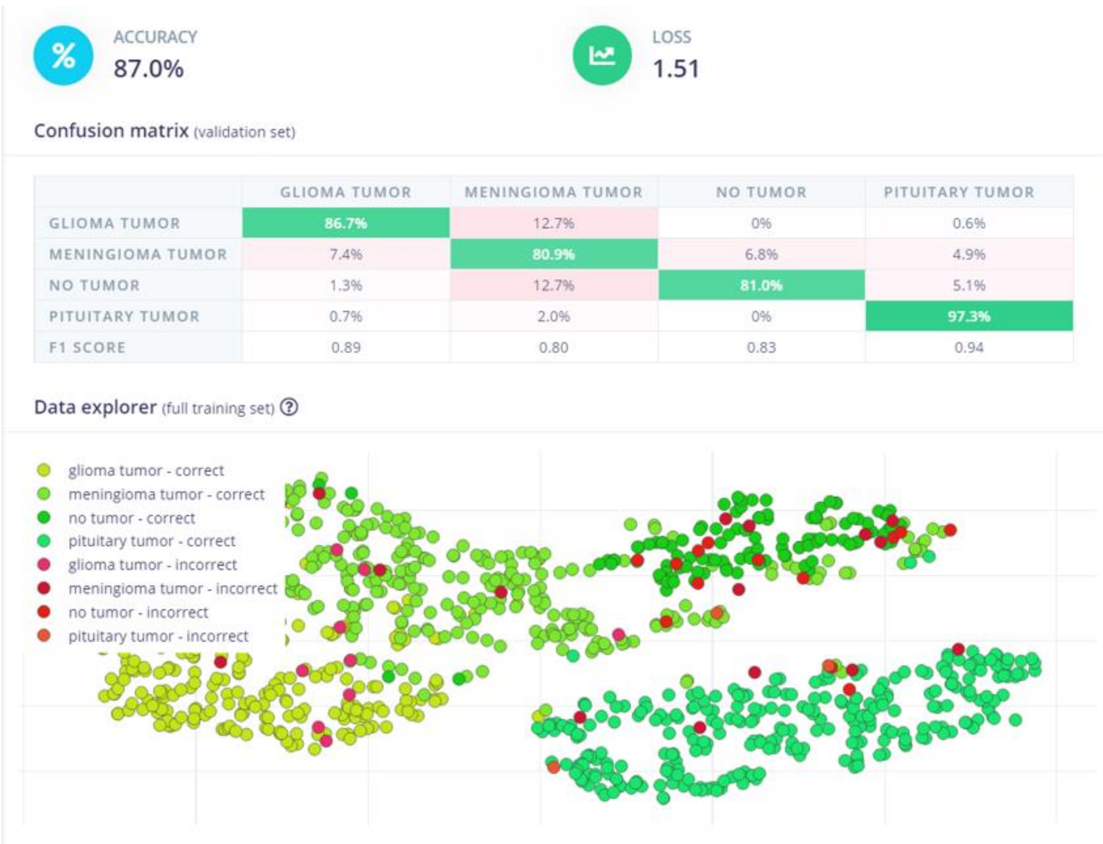

Figure 3. The performance of the model when the learning rate is equal to 0.002.

The experimental findings showed that the accuracy of the outcomes gradually increases as the learning rate rises from 0.0005 to 0.002. This may be due to overfitting that occurs when the learning rate is set too low, leading to a decline in the accuracy of the results. When the learning rate decreased from 0.003 to 0.002, the accuracy of the results increased. This indicates that in this interval, when the learning rate is set at a low level, the range of each parameter update is small, the training process is more stable, and the optimal solution can be found more easily, thus improving the training accuracy. The experimental results show that the convolutional neural network training model for brain tumor recognition has a high accuracy and can better identify different types of brain tumors. As shown in Figure 4, the study sampled a picture from the data set and conducted real-time classification, finally obtaining a satisfactory result. Nevertheless, the results of this study possess certain limitations. While the model trained in this investigation is more efficient than manual classification, it still demonstrates lower recognition accuracy rates for meningioma tumor and no tumor. Thus, improving these aspects remains a critical objective for future research.

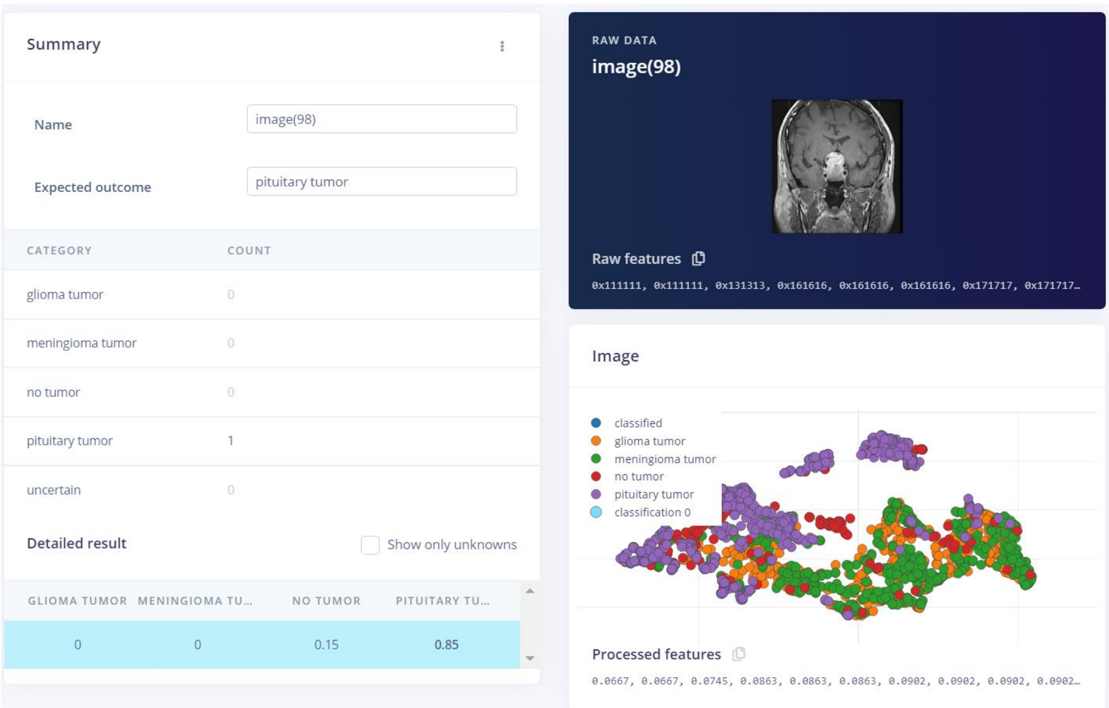

Figure 4. The result based on the sample image.

4. Conclusion

In this paper, the brain tumor recognition model is trained to recognize various brain tumors, aiming to identify and classify a large number of images of various kinds of brain tumors. The study used convolutional neural network to train the model and experimented with different learning rates. Four sets of experiments were used to evaluate the suitable method. In the end, this study obtained an optimal result that can identify brain tumors with high efficiency and high accuracy. In the future, further study plans to implement different convolutional neural network architectures to train the model, so as to further improve the accuracy of recognition.

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