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Classification of brain tumors based on magnetic resonance imaging (MRI) using deep learning models

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Abstract. Nowadays, With the advancements in medical care and the improvement in global living standards, there has been a continuous increase in the average life expectancy of people around the world, and the aging problem is constantly aggravated, brain tumors have become a growing global health problem. The project aims to use deep learning models to classify magnetic resonance imaging (MRI) images of brain tumors. By constructing convolutional neural network model, image feature extraction and classification are carried out. Data preprocessing, data enhancement, Adaptive Moment Estimation (Adam) are used to improve the model performance, plot the accuracy curve and generate the confusion matrix, and visualize the classification performance of the model. Possible future tasks may include optimizing the model architecture and expanding the exploration of data augmentation techniques to bolster the model's performance, while also further investigating the model's interpretability to understand the internal mechanisms of the model when making predictions. In addition, the project has great application potential, and the model can be applied to the actual clinical assisted diagnosis system, which has good scalability and application prospect. By using deep learning model and related technologies, the accuracy of brain tumor classification can be improved in clinical diagnosis, and better diagnosis and treatment services can be provided for the majority of brain tumor patients.

Keywords: Magnetic Resonance Imaging, Adaptive Moment Estimation, Brain Tumors, Deep Learning.

1. Introduction

In today's world, brain tumor is a disease that poses a great threat to human health. It is considered as one of the deadliest cancers, posing a significant threat to life.[1] Brain tumors can occur in the brain, cerebellum, meninges, and ventricles, and are of various types, including malignant and benign tumors. According to the data, there was a significant rise in the incidence of brain cancer in the United States, with the number of cases increasing from 1.5 million in 2013 to 1.658 million in 2015 [2]. There were nearly 16,830 deaths from brain tumors in 2018 [3]. According to the American Cancer Society's recently released "Cancer Statistics 2020," an estimated 19,000 people in the United States will die from brain tumors in 2020 [4]. Early, identification and treatment of brain tumors are critical to survival and recovery. However, given the specific location and complexity of brain tumors, their diagnosis and treatment remain challenging. The problem of brain tumors has become one of the important challenges of contemporary medicine, which seriously affects the health and quality of life of patients. Therefore, the importance of identifying brain tumors has become particularly prominent.

Over the past few years, scientists and doctors have devoted themselves to studying brain tumors and have made remarkable progress. At present, some medical imaging technologies have been successfully used to observe, analyse, diagnose, monitor and treat human diseases, such as magnetic resonance imaging (MRI), computed tomography (CT), ultrasonic imaging (UI) and X-ray [5]. Among them, MRI brain tumor segmentation is the most extensive and important content in the field of medical images. Researchers have proposed many segmentation methods for MRI brain tumors. Rao et al. used a kernel-based support vector machine (SVM) to construct a model for detecting and classifying brain tumor MRI images, and proposed an efficient method for accurate detection and classification of brain tumors [6]. Dipu et al. utilized both the You Only Look Once (YOLO) and FastAi deep learning methods and their study effectively accomplished precise detection and classification of brain tumors [7]. Raja et al. used mixed depth autoencoders of Bayesian fuzzy clustering segmentation method to classify brain tumors [8]. Zhu et al. performed automatic classification of brain tumors based on ResNet [9]. Considering the size and complexity of the dataset, as well as computational resources, this paper uses convolutional neural network(CNN) to construct a model to recognize and classify brain tumor MRI images

The main goal of this research is to introduce CNN to construct an analytical model for accurate brain tumor recognition. CNN has significant advantages in image processing and feature extraction, which can help researchers process brain tumor images and extract features for recognition. CNN can represent the input efficiently without the need for a priori artificial features. The powerful feature representation capability motivates the model to summarize and make recognition effectively. Experimental results show that the CNN-based brain tumor recognition model performs well in accuracy and robustness. In particular, after pre-processing using data enhancement techniques and image segmentation algorithms, the model has made significant progress in brain tumor recognition. This study is of great practical significance for improving the early detection rate, accuracy, and treatment outcome of brain tumors, and is expected to provide better support and decision-making basis for doctors and patients in clinical practice.

2. Methodology

2.1. Dataset description and preprocessing

The dataset employed in this study for training and evaluation purposes, called BRAIN TUMOR MRI DATASET, is obtained from Kaggle, is obtained from Kaggle [10]. This dataset is compiled by integrating data from figshare, SARTAJ dataset, and Br35H, which contains 7023 MRI images of the human brain, each with a size of 512×512 pixels. The brain tumor portion of the images is essentially centered and takes up about the same space in each image. The dataset contains images of four types of brain tumors: (1) lioma, 2) meningioma, (3) ontumor, (4) pituitary gland.

The dataset is characterized by the brain tumor images themselves, and the label is the category information corresponding to the brain tumor. The training set contained 5712 images, 4 types of brain tumor images were organized into different folders, and the test set contained 1311 samples. Figure 1 provides MRI images of 4 types of brain tumors.

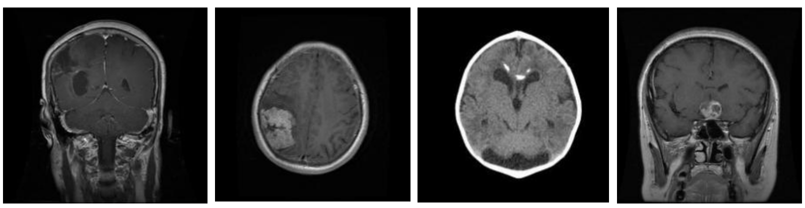

Figure 1. MRI images of brain tumors.

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2.2. Proposed approach

The brain tumor classification method proposed in this paper is mainly implemented based on CNN, which is a classical deep learning algorithm. Through convolution and pooling operations, CNN can extract key features from images to help the model accurately classify brain tumors. After training and evaluation, the CNN model shows high accuracy and performance in brain tumor classification tasks. Figure 2 below illustrates the structure of the system.

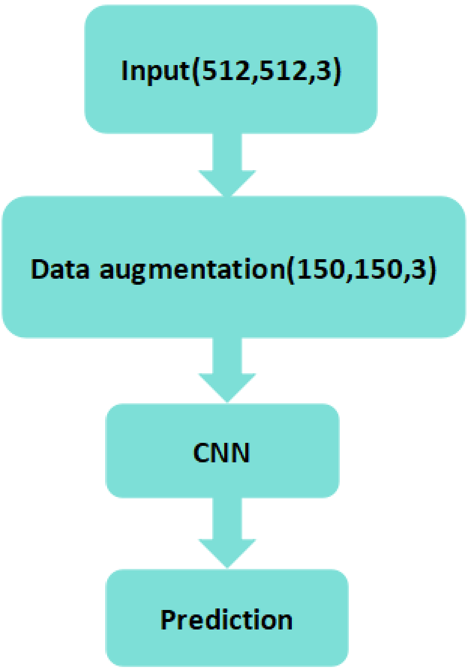

Figure 2. The pipeline of the model.

2.2.1. CNN. The image size is adjusted before input, the size is (150,150,3). The model's convolutional base comprises 4 Conv2D layers and 4 Max pooling layers, with the number 3 indicating the quantity of channels. Use the convolution layer and pooling layer as feature extractors. In this neural network architecture, 32 convolutional kernels with dimensions of (3, 3) are utilized. The convolutional layer leverages sliding windows to conduct convolution operations on the input images, thereby extracting local features from various locations. The activation function uses Rectified Linear Unit (ReLU), which turns all negative values to zero and preserves positive values. The pooling layer subsamples the feature graph obtained after convolution to retain important features and reduce the number of parameters. In this neural network, Windows with the size of (2, 2) are used for maximum pooling operation, during the maximum pooling operation, the highest value within each window is retained, while other values are discarded. In this neural network, there are two repeated convolution and maximum pooling operations, gradually extracting higher-level features. The number of convolution cores doubles each time the convolution operation is repeated. The first repeat has 64 convolutional nuclei, and the second and third repeats each have 128 convolutional nuclei. Through multiple convolution and pooling operations, the neural network can learn more abstract and advanced image features.

The flattening layer takes the output feature map from the previous pooling layer and converts it into a one-dimensional vector by flattening its structure. In this way, the image data can be converted into one-dimensional feature vectors, which is convenient for the subsequent processing of the full connection layer. The fully connected layer connects the flattening feature vector with the weight for

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linear transformation. In this neural network, there are 512 neurons in the fully connected layer. After the linear transformation, the activation function adopts ReLU. The Dropout layer has been added to the model to randomly drop a subset of neurons with a 50% probability, which reduces overfitting. The image goes through a series of transformations before being fed into the network. These methods include image normalization, random rotation, random panning, cropping, scaling, horizontal flipping, vertical flipping, and fill. The purpose of these transformations is to increase the diversity of the training data and give the model better generalization ability. With CNN, features can be extracted from input images using convolution and pooling operations, thus achieving good detection and classification of brain tumors. The neural network architecture is depicted in Figure 3, illustrating its structure and components.

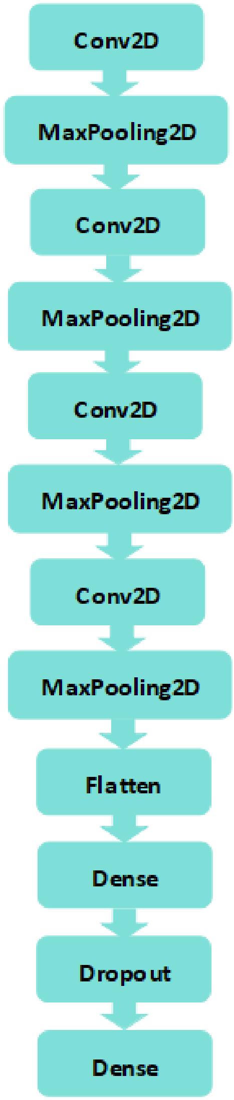

Figure 3. The architecture of the neural network.

2.2.2. Loss function. The loss function holds significant importance in training and optimizing the model. For classification tasks, the classification cross-entropy loss function is optimal because it is efficient in multi-class classification problems. Therefore, for training the model in this project, the decision is made to employ the classification cross-entropy loss function, which serves the purpose of assessing the disparities between the model's predictions and the actual labels throughout the training process. Subsequently, the model's weights are adjusted based on these disparities to refine its performance. By minimizing the loss function, the model can gradually adjust its parameters, making the prediction results closer to the real label, thus improving the accuracy of the model. Training the model involves utilizing the loss function as a guide and optimizer to attain optimal outcomes, as,

$$C = -1/n * \sum(y * \log(y\_hat)) \tag{1}$$

The above formula denotes the Categorical Cross-entropy loss, where y represents the actual label, representing the real classification label of each training sample. In the brain tumor detection task, it is a probability distribution vector where only the correctly classified labels are 1 and the rest are 0. y_hat represents the model's forecast output, which is also a probability distribution vector representing the model's categorical predictions for each category. For each sample, the disparity between the actual label y and the model's predicted output y_hat is evaluated by taking the logarithm, followed by summation and averaging. The resulting value C represents the average loss of the model over the entire training dataset.

2.3. Implemented details

This project has done the following details to improve the performance of the model: various data enhancement operations have been carried out on the training image, including random rotation, translation, scaling, flipping, etc. The goal is to increase the diversity of the training data so that the model is more robust to images at different angles and scales. In data preprocessing, this project normalizes the pixel value of the image and scales it to between 0 and 1. This speeds up the model convergence and training process. During training, a portion of the training data is set aside as a validation set. This independent subset is utilized to assess the model's performance and fine-tune hyperparameters as necessary. This avoids overfitting of the model in training and provides a reliable evaluation index. The project selected Adaptive Moment Estimation Adam) as the optimization algorithm of the model. Adam combines momentum and adaptive learning rate, and can automatically adjust the learning rate during training, thus speeding up the convergence speed of the model. To prevent overfitting in the model, a Dropout layer is introduced before the fully connected layer. During training, Dropout randomly deactivates a portion of neurons, thereby promoting generalization and reducing reliance on specific neurons.

3. Result and discussion

In this study, brain tumors are classified from more than 7,000 brain tumor images using the CNN model described above. The images were divided into four categories, with the category of brain tumor as the label. Figure 4 illustrates the variations in model accuracy, while Figure 5 demonstrates the fluctuations in model loss throughout the training and validation process.

From Figure 4, By observing the evolution of training and validation accuracy over increasing rounds of training, it becomes apparent that the CNN model achieves stability in accuracy after several iterations. Notably, there exists minimal disparity between the accuracy obtained from training and validation sets, which indicates that the model does not have overfitting problems and shows superior performance in the task of classifying brain tumors. In Figure 5, As the number of training iterations decreases, the fluctuation in training and validation losses is observed to change. the losses of both the training set and validation set decrease and tend to be stable, indicating that the model has good learning ability and generalization ability. The CNN model can automatically learn discriminative features from images. By stacking multiple convolutional layers and pooling layers, the network can effectively extract local and global features in images, to classify different types of tumors. The overall performance of the model was enhanced through pre-training of the CNN backbone, which involved the implementation of learning rate optimization, data augmentation, and Dropout regularization techniques, and the final verification accuracy reached 96%, which highlights the high accuracy and reliability of CNN in classifying tumor types in brain MRI images.

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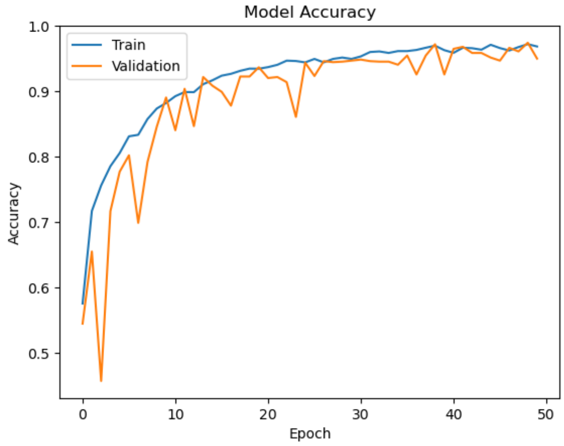

Figure 4. The model accuracy.

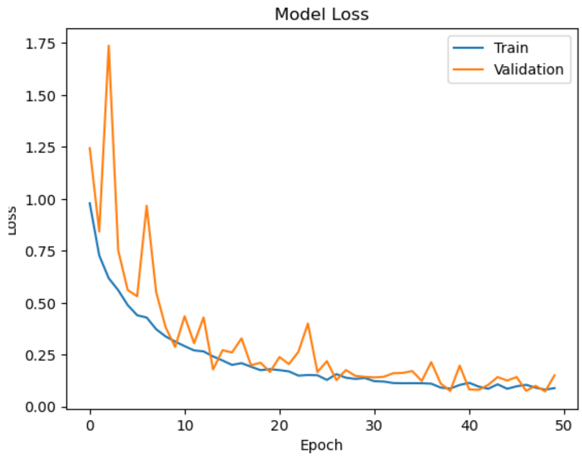

Figure 5. The model loss.

Figure 6 above provides an evaluation of the model's performance on different categories using the confusion matrix. Upon examining the confusion matrix, it becomes evident that the model exhibits high accuracy in predicting the notumor class. However, there is some confusion observed in the classification between glioma and meningioma. This observation may be because glioma and meningioma may have similar appearance features on images, making it difficult for models to accurately distinguish. This also means adding more training data to help the model learn the subtle differences between them.

In conclusion, the CNN model has exhibited exceptional capabilities in classifying brain tumors. The accuracy curve and confusion matrix provide intuitive evidence of the model's strong performance in this task, and also indicate the direction for further improvement. In future studies, more training data can be considered to help the model learn. Alternatively, use a more complex feature extraction method or select a pre-trained deep learning model (such as ResNet, Inception, etc.) to extract image features to improve the model's ability to distinguish between glioma and meningioma.

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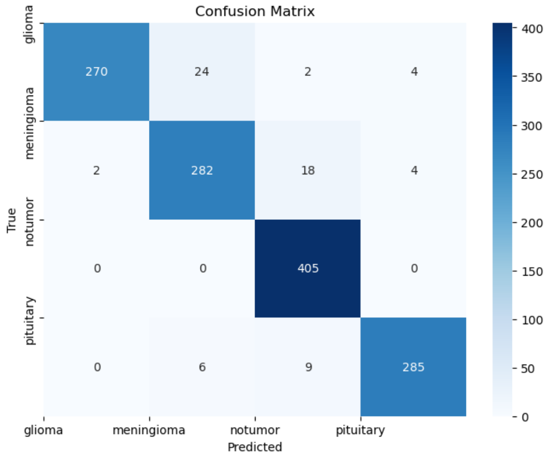

Figure 6. The confusion matrix of the model.

4. Conclusion

The purpose of this study is to classify brain tumor MRI images in the BRAIN TUMOR MRI DATASET based on the CNN model and predict the type of brain tumor according to the MRI images. The deep learning model CNN is used for image classification. Data enhancement and preprocessing of training images are performed. The model construction involves incorporating key layers such as convolution, pooling, fully connected, and Dropout layers within a deep learning architecture. To compile and train the model, the Adam optimizer is utilized in conjunction with the classification cross-entropy loss function. The accuracy rate reaches 96%, and the brain tumor classification task performs well. Future studies consider more complex brain tumor classification tasks, further explore better feature extraction methods, and try to use other deep learning models to extract features and enhance adaptability to complex tasks.

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