

# Research on Brain Tumor Medical Image Classification Based on Deep Neural Network

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## ABSTRACT

This paper mainly discusses the use of deep neural networks in classifying medical images for brain tumors. Firstly, the research background is introduced, pointing out the importance of early and accurate diagnosis of brain tumors and the limitations of traditional manual analysis methods. With the development of deep neural networks, it shows great potential in the field of medical image classification. Then, the basic principles of deep neural networks are expounded. The characteristics of medical image classification are analyzed, such as the specific features of brain tumor images and the strict requirements for data quality and annotation. Then, the utilization of deep neural networks for the categorization of brain tumor images is introduced in detail: deep neural learning image classification on MATLAB taking CNN as an example. The advantages and challenges of deep neural networks in the classification of brain tumor images are discussed. Finally, the research conclusions are summarized. Deep neural networks have achieved remarkable results in the classification of medical images for brain tumors, but there are also deficiencies. The future research directions are prospected.

## KEYWORDS

Deep neural network; Brain tumor; Medical image classification

## 1. INTRODUCTION

As a serious neurological disease, early and accurate diagnosis of brain tumor is crucial for the treatment and prediction of patients. According to statistics, millions of people around the world are affected by brain diseases every year. In 2020, there were about 80000 new cases and 65000 deaths of brain tumors in China. The age standardized incidence rate and mortality rate were 4.1/100000 and 3.2/100000 respectively [1]. According to data from the National Cancer Institute in the United States, the mortality rate of brain tumors is very high, with a 5-year survival rate of only 36%.

Medical images play a crucial part in the diagnosis of brain tumors, but traditional manual analysis methods have many limitations, one is that the results of imaging diagnosis are often influenced by the experience, skill and subjective judgment of doctors, and different doctors may interpret the same image differently, resulting in diagnostic differences. Second, the results of imaging diagnosis are often influenced by the doctor's experience, skills, and subjective judgment, and different doctors may interpret the same image differently, resulting in diagnostic differences.

With the development of deep neural networks, they have shown great potential in the area of medical image classification. According to the data published in the CA (A Cancer Journal for Clinicians),

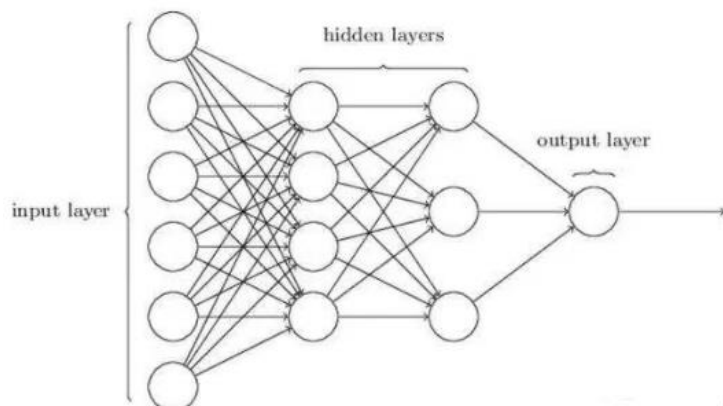
there were 19.29 million new instances of cancer around the world in 2020, and the clinical diagnosis of brain cancer is very difficult [2]. Brain tumors include meningiomas, gliomas and pituitary tumors, and treatment for different types of brain tumors varies greatly. Deep neural networks can automatically extract image features through the learning of a large number of brain tumor medical image data to achieve accurate classification of different kinds of brain tumors.

For example, the deep neural network brain tumor image classification method based on transfer learning can classify patients with different brain tumors through data preprocessing, building pre-trained models, improving CNN architecture models, and brain tumor image classification evaluation. The use of classified brain tumor MR images can assist doctors in diagnosis, help patients detect the disease in advance, and improve the efficiency of doctors' diagnosis.

At present, considerable progress has been achieved in the application of deep learning in medical image analysis. Deep neural networks play an important role in image classification and recognition, image segmentation, image denoising, enhancement and reconstruction, and real-time processing. In medical image classification of brain tumors, deep learning models like convolutional neural networks (CNNs) are able to learn and identify tumor lesions in MRI images, providing doctors with more accurate and faster diagnostic support [3].

## 2. THEORETICAL BASIS

Deep neural network is a calculating model which imitates the structure and function of human brain neural networks, and plays an important role in image classification. It learns the complex features of the input data through multiple hidden layers and nonlinear activation functions, so as to achieve efficient learning and prediction of complex tasks [4].



**Figure 1.** Illustration of deep neural networks

In the training process, forward propagation is carried out firstly, and the input data is passed from the input layer to the output layer through the hidden layer in turn, and the prediction result is obtained. The error between the predicted result and the true label is then calculated, typically using a loss function to measure the magnitude of the error. Then, backpropagation is carried out, starting from the output layer, the error is backpropagated to each layer of neurons in turn, and the gradient of each neuron is calculated according to the error, that is, the direction of change of the weight and bias terms. Finally, optimization algorithms, such as gradient descent algorithm, are used to update the weights and bias terms according to the gradient, so that the prediction results of the network are gradually close to the real label.

For example, in a simple two-layer neural network, the input layer has two neurons, the hidden layer has three neurons, and the output layer has one neuron. Let's say the input data is [0.5, 0.8] and the true label is 1. In the forward propagation process, the input data is handled by the weighted summation and activation function of the hidden layer to obtain the output of the hidden layer. Then,

the output of the hidden layer is processed by the weighted summation and activation function of the output layer to obtain the prediction result. Let's assume that the prediction outcome is 0.7. The error between the predicted result and the true label is calculated, assuming that the mean square error is used as the loss function with an error of  $(0.7 - 1)^2 = 0.09$ . Backpropagation is then performed, starting from the output layer and calculating the gradient of neurons in the output layer. According to the chain rule, the gradient of the output layer neuron is equal to the partial derivative of the error to the output layer neuron multiplied by the partial derivative of the activation function to the input. Suppose the activation function of the output layer neuron is a sigmoid function, the derivative of which is the output multiplied by  $(1 - \text{output})$ . Then the gradient of the neurons in the output layer is  $2 \times (0.7 - 1) \times 0.7 \times (1 - 0.7) = -0.126$ . The error is then backpropagated to the hidden layer, and the gradient of the hidden layer neurons is calculated. Also, according to the chain rule, the gradient of the hidden layer neuron is equal to the gradient of the output layer neuron multiplied by the weight of the hidden layer to the output layer multiplied by the partial derivative of the activation function on the input. Assuming that the activation function of the hidden layer neuron is also a sigmoid function, the gradient of the hidden layer neuron can be calculated sequentially. Finally, the gradient descent algorithm is used to update the weights and bias terms according to the gradient. Assuming a learning rate of 0.1, the updated formula for weights and bias items is  $\text{Weight} = \text{Weight} - \text{Learning Rate Gradient}$ ,  $\text{Bias} = \text{Bias} - \text{Learning Rate Gradient}$ . After multiple iterations of training, the prediction results of the network will gradually approach the real label.

In short, deep neural networks can automatically learn the features of input data through training algorithms such as neuron connection and backpropagation, so as to achieve efficient learning and prediction of complex tasks. In the medical image classification of brain tumors, deep neural networks can automatically extract image features through the learning of a large number of brain tumor medical image data to achieve accurate classification of different types of brain tumors [5].

### **3. APPLICATION OF DEEP NEURAL NETWORK IN BRAIN TUMOR IMAGE CLASSIFICATION**

#### **3.1. Dataset Preparation**

The preparation of datasets is crucial in the task of image classification of brain tumors based on transfer learning. A dataset of 3064 brain tumor images was imported into this experiment, which then needed to be preprocessed. Both datasets are normalized to 256x256 pixels, which can make different images consistent in size and gray value, which is convenient for the training of deep neural networks. The process of normalization can take common approaches, such as scaling the pixel values of an image to the  $[0, 1]$  interval or normalizing to a distribution with a mean of 0 and a variance of 1.

Normalization formula:  $x' = (x - \mu) / \sigma$

```

testData = struct(fields{:});

% Copy the field name and data
for i = 1:numel(fields)
    fieldName = fields{i};

    % Initializes the field array
    trainFieldArray = cell(numTrain, 1);
    testFieldArray = cell(numTotal - numTrain, 1);

    for j = 1:numTotal
        if j <= numTrain
            trainFieldArray{j} = dataStructArray(idx(j)).(fieldName);
        else
            testFieldArray{j - numTrain} = dataStructArray(idx(j)).(fieldName);
        end
    end

    % Assigns the cell array to the struct field
    trainData.(fieldName) = trainFieldArray;
    testData.(fieldName) = testFieldArray;
end

% Displays the size of the partitioned dataset
fprintf('Training set size: %d\n', numTrain);
fprintf('Test set size: %d\n', numTotal - numTrain);

%trainData and testData now contain divided training set and test

```

Training set size: 2451  
Test set size: 613

**Figure 2.** 3064 data were imported into MATLAB library and divided into test group and training group

In addition, For the purpose of enhancing the diversity of data and the generalization ability of the model, data augmentation techniques can also be adopted. For example, the image can be rotated, flipped, cropped, and its brightness, contrast, and saturation can be adjusted. Through these data augmentation methods, the dataset can be effectively enriched and the robustness of the model can be improved.

### 3.2. Model Construction and Fine-Tuning

Model construction is a key step in deep neural network image classification of brain tumors. First, prepare a brain tumor MR image dataset as the target dataset.

The brain tumor MR image dataset was fed into a pre-trained network model, and the pre-trained model was invoked. Pretrained models are typically trained using large-scale image datasets like ImageNet. and have learned rich image features. Through the method of transfer learning, the weights and parameters of the pre-trained model are applied to the brain tumor image classification task, which can greatly reduce the training time and improve the model performance.

Then, the pre-training parameters were set to fine-tune the weights obtained from the pre-training, so that the extracted classification features were closer to the brain tumor dataset. During the fine-tuning process, the weights of some layers of the network, such as the last few fully connected layers or partially convolutional layers, can be adjusted to suit the specific characteristics of the brain tumor image. At the same time, A small learning rate can be used. for fine-tuning to avoid disruption to the pre-trained model.

Finally, an improved CNN architecture model is trained.

Convolutional layer formula:  $z=(W*x)+b$

Where  $W$  is the convolution kernel,  $x$  is the input feature map,  $b$  is the bias term, and  $*$  represents the convolution operation.

Activation layer (e.g. ReLU):  $a=\max (0, z)$ .

Pooling layer (e.g., maximum pooling):  $p = \max(x_i, j)$

Fully connected layer:  $y = W'a + b'$

Where  $W'$  and  $b'$  are the weights and biases of the fully connected layer, respectively.



**Figure 3.** The result of the model

During training, the result of the model on algorithms and optimization algorithms such as stochastic gradient descent can be used to update the weights and parameters of the model to minimize the loss function. Through continuous iterative training, the model gradually learns the features of brain tumor images and improves the accuracy of classification.

Gradient descent update rule:  $W = W - \alpha \partial L / \partial W$

where  $\alpha$  is the learning rate, and  $\partial L / \partial W$  is the gradient of the loss function with respect to the weights.

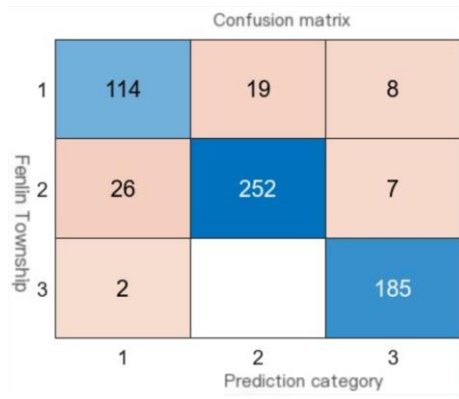
To evaluate the performance of the model, it could be validated separately using cropped and unclipped datasets. Classification performance is evaluated by calculating indicators such as accuracy, loss, precision, and recall. If the model performance is not satisfactory, the model structure and parameters can be further adjusted, or other data augmentation methods and optimization algorithms can be used until a satisfactory classification effect is achieved.

Cross-entropy loss formula:

$$L = -\sum_{i=1}^C y_i \log(P_i)$$

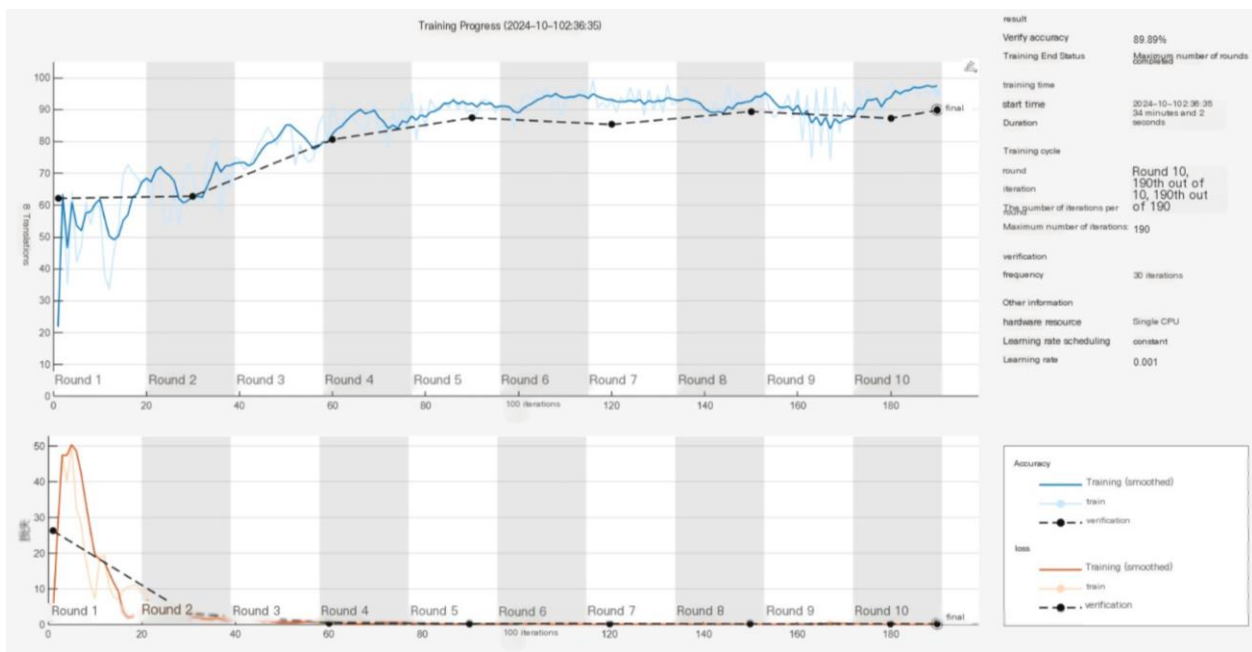
where  $C$  is the number of categories,  $y_i$  is the one-hot representation of the real label, and  $p_i$  is the probability predicted by the model.

Through reasonable dataset preparation and model construction and fine-tuning, deep neural networks can be effectively used for brain tumor image classification, which provides significant support for the identification and treatment of brain tumors.



**Figure 4.** Classification matrix diagram

### 3.3. Analysis of Results



**Figure 5.** Graphs of training and test results

The model was trained for 10 rounds with 19 iterations each, with a maximum of 190 iterations. The validation accuracy is 89.89%, which is a relatively high level of accuracy. The results reveal that the model has reached certain results in image classification tasks, but there is still room for improvement. By further optimizing the model structure, data, and hyperparameters, the performance and practicability of the model can be improved, and a better solution can be provided for the application of image classification.

## 4. DISCUSSIONS

### 4.1. Advantage Analysis

#### 4.1.1. High accuracy

Deep neural networks have shown high accuracy in brain tumor image classification. Compared with traditional artificial analysis methods, deep neural networks can automatically learn and extract complex features in images, avoiding errors caused by human factors. For example, the deep neural network brain tumor image classification method based on transfer learning can accurately classify

different types of brain tumors by learning from a large number of labeled data. Deep neural networks can learn more comprehensive and accurate features from a large number of medical image data of brain tumors, thereby improving the accuracy of classification.

#### 4.1.2. Efficiency improvement

Deep neural networks greatly improve the diagnostic efficiency in brain tumor image classification and reduce the workload of doctors. On the one hand, deep neural networks are able to quickly classify a large number of brain tumor images in a short span of time. On the other hand, deep neural networks can process image data automatically, greatly reducing the workload. In addition, deep neural networks can also update and learn the latest medical research results in real time, continuously improve their diagnostic capabilities, and provide more accurate and faster diagnostic support.[6]

## 4.2. Discussion of Challenges

### 4.2.1. Data Quality and Annotation

In the process of applying deep neural networks to brain tumor image classification, data quality and annotation face many problems. First of all, medical image data is expensive to obtain, especially high-quality brain tumor image data. Obtaining this data often requires specialized medical equipment and technicians, and requires patient cooperation, which makes data collection difficult.

The challenges of annotation are mainly in terms of accuracy and consistency. The annotation of medical images needs to be carried out by professional doctors, and the professional level, experience and labeling standards of different doctors may be different, which leads to subjectivity and inconsistency in the annotation results. For example, for the same brain tumor image, different doctors may give different annotation results, which brings great difficulty to the training of the model. Studies have shown that the inconsistency of medical image annotation can be as high as more than 20%.

In order to solve the problem of data quality and annotation, the following improvement directions can be taken. On the one hand, A larger-scale brain tumor image classification dataset can be established. Through multi-center cooperation and data sharing, the brain tumor image data of different medical institutions can be integrated to expand the scale of the dataset. For example, several international cooperation projects are already trying to establish a global database of brain tumor images to provide researchers with more annotated data. On the other hand, automated annotation tools are introduced. Using artificial intelligence technology to develop tools that can automatically annotate medical images can greatly improve the efficiency and accuracy of annotation. For example, some deep learning-based image annotation algorithms have been able to achieve preliminary annotation of brain tumor images, although doctors still need to review and correct, but they have greatly reduced the workload of doctors [7].

### 4.2.2. Model interpretability

The explanatory problem of deep neural network models in brain tumor image classification has always been a challenge. Because deep neural networks are often seen as "black boxes" with a lack of explanation and transparency, it is difficult for doctors to understand the model's decision-making process, which is especially important in the medical field. If doctors do not understand the basis for the model's decision-making, it is difficult to trust and apply the model's outputs.

In order to improve the interpretability of deep neural network models, the following methods can be adopted. One way to do this is to explore explainable model architectures. For example, a model based on an attention mechanism allows doctors to represent the parts of the image visually that the model focuses on during the classification process, so as to understand the basis of the model's decision-making. Another approach is to develop specialized interpretive tools. These tools can help doctors understand the decision-making process of deep neural network models through visualization,

feature analysis, and more. For example, some visualization tools can display the features learned by the model in the form of images, allowing doctors to visualize the image features that the model is focusing on during the classification process.

In addition, the interpretability of the model can be improved by multimodal data fusion. In addition to medical image data, multimodal data such as clinical data (such as age, gender, medical history) and laboratory test results (such as blood routine, tumor markers, etc.) can also be fused. This allows doctors to understand the decision-making process of the model from multiple perspectives, improving the explanatory and credible nature of the model. For example, in brain tumor image classification, if the model takes into account not only image features, but also factors such as the patient's age, gender, and medical history, doctors can better understand the basis of the model's decision-making, so that they can trust and apply the model's output more trusting.

## 5. CONCLUSIONS

Deep neural networks have achieved remarkable results in medical image classification of brain tumors. Through data preprocessing, building pre-trained models, improving CNN architecture models, and brain tumor image classification evaluation, patients with different brain tumors can be accurately classified.

However, deep neural networks also have some shortcomings in brain tumor image classification. In terms of data quality and annotation, the acquisition cost of medical image data is high, and the accuracy and consistency of annotation are difficult to guarantee. According to statistics, the cost of obtaining a high-quality medical image data of brain tumor may be as high as hundreds or even thousands of yuan, and the inconsistency of medical image annotation may be as high as more than 20%. In terms of model interpretability, deep neural networks are often seen as a "black box", making it difficult for doctors to understand the model's decision-making process.

In general, deep neural networks have brought new opportunities and challenges to medical image classification for brain tumors. In the future, we need to further explore more effective data preprocessing methods, optimize network structure and parameter settings, improve data quality and annotation accuracy, and enhance the explanatory nature of models, so as to better play the role of deep neural networks in the diagnosis and treatment of brain tumors. At the same time, multi-center cooperation, data sharing, and the development of automated annotation tools will help solve the problems of data quality and annotation. Through continuous research and innovation, deep neural networks are expected to provide more accurate and efficient diagnosis and treatment options for brain tumor patients.

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