An Application of Prior Knowledge on Detection of Brain Tumors in Magnetic Resonance Imaging Images

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Abstract. Brain diseases, such as brain tumors, are essential problems in people's health. As a result, brain tumor detection has become a demanding and challenging task. In this paper, an interpretable method is proposed to introduce the prior knowledge of magnetic resonance imaging (MRI) images to brain tumor detection along with a pre-trained ResNeXt50(32×4d). Experiments are conducted over 7 different seeds and 6 different epochs. An outstanding accuracy of 95.13% was achieved on the test dataset. Compared with the traditional training method, this method improves the performance by 0.83% in the best case. Experimental results indicate that prior knowledge enhances performance on brain tumor detection by about 0.5% overall, proving that this method is useful and be of value for reference.

Keywords: Brain tumors · deep learning · prior knowledge · MRI images

1 Introduction

Because it regulates most human functions such as memory, speech, thoughts, and leg and arm motions, the human brain is the most essential element of the body [1]. Brain diseases, mainly caused by abnormally growing brain cells, or brain tumors, bring about brain cancer. Cancer is the largest cause of mortality in the globe, accounting for approximately 10 million fatalities in 2020, or roughly one out of every six deaths [2]. Brain cancer is the main cause of cancer mortality among adolescents and young adults, and the second greatest cause overall, behind breast cancer [3]. Therefore, brain tumors are an essential problem in the medical area and in people's lives.

Magnetic Resonance Imaging, widely known as MRI, is a technique that is broadly used in medical areas. It uses magnetic resonance phenomena to capture electromagnetic signals so that structures in human bodies are able to be rebuilt layer by layer. In MRI, there are mainly four weighting methods: T1, T2, T1ce, and Flair. T1 displays the brain anatomy clearly since the white matter is white, the gray matter is grey, and the cerebrospinal fluid is black. The T2 weighting method is strongly related to water contained in tissues, so the white matter is grey, the grey matter is white, and the cerebrospinal fluid is bright white. Additionally, since abnormal cells usually contain more water than normal ones, diseased cells are shown clearly in T2-weighted MRI images. As a result,

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doctors can easily locate the tissues in question. T1ce is partly the same as T1. The difference is that agents are injected into the blood so that places with abundant blood supply are white. It can not only show the tumor location and other features nearby, but it can also further display structures inside the tumor. Flair uses techniques to suppress signals released by cerebrospinal fluid, so diseased cells near the cerebrospinal fluid can be identified without any difficulty.

Some brain tumors grow in the center of the brain, the place of cerebrospinal fluid. It is difficult to distinguish brain tumors from cerebrospinal fluid in these images if they are T2-weighted, since both brain tumors and cerebrospinal fluid are bright white. As a result, weighting methods are concerned with the model performance. This paper presents an interpretable method to introduce a prior knowledge of magnetic resonance imaging(MRI) images into brain tumor detection in combination with pre-trained ResNeXt50 (32×4d). A series of experiments were conducted to compare the performances of two cases:

1. Training the model on the original dataset.
2. Training the model on the dataset with additional information about the weighting method of MRI images.

With the higher accuracy of brain tumor detection, patients are able to get fast and accurate detection results, saving both patients' and doctors' time. As a result, brain tumors can be detected earlier, which will be helpful to save more people from the deaths caused by brain tumors.

2 Related Work

The idea of this paper is derived from the concepts below.

Transfer Learning
Transfer learning, which focuses on transferring knowledge across domains, is a potential machine learning method for addressing the issue of training data distribution differing from test data distribution [4]. In Brain tumor classification for MR images using transfer learning and fine-tuning [5], To classify brain tumors, a pre-trained deep CNN model and a block-wise fine-tuning technique based on transfer learning are used.

Multitask Learning (MTL)
Multitask learning is an inductive transfer strategy that increases generalization by incorporating domain knowledge contained in related task training signals as an inductive bias [6]. MTL has been applied to both brain tumor classification and brain tumor segmentation. In Multi-task learning for brain tumor segmentation [7], three related tasks, tumor segmentation, image reconstruction, and detection of enhancing tumor are trained concurrently using a common encoder. In Brain tumor classification by cascaded multi-scale multitask learning framework based on feature aggregation [8], a method for segmenting and classifying brain tumors in MRI images is given. In Multi-task deep learning based ct imaging analysis for COVID-19 pneumonia: classification and segmentation

[9], reconstruction, segmentation, and classification are trained at the same time to solve problems in COVID-19 and lung cancer.

Auxilliary Learning
Each task in MTL has the same priority, all of which should achieve high test accuracy. However, different from MTL, in auxiliary learning, auxiliary tasks only serve to learn a rich and robust common representation of an image. The system will be strengthened throughout training by selecting tasks that are simple to learn and complement the primary task [10]. In Multi-task learning for small brain tumor segmentation from MRI [11], to improve their model for tiny tumor size, a U-module was introduced to their model as an auxiliary task, which helps maintain properties of small-sized tumors.

3 Methodology

3.1 Dataset

The dataset that has been used in the experiments is based on the Brain MRI Images for Brain Tumor Detection dataset on Kaggle [12]. The used dataset contains MRI images of the four different weighting methods mentioned above. The original dataset consists of two classes(TUMOR and NO-TUMOR) in two folders (yes, no). After removing duplicate images, there are 141 images of brains with tumors in the folder "yes" and 86 images of brains without tumors in the folder "no". To make training easier and for the sake of multi-label training, these images are put in one folder and a csv file is generated to map image names and corresponding labels.

3.2 Training Strategy

In the training strategy, the dataset is divided into four parts, in which the ratio of TUMOR and NOTUMOR(NORMAL) is approximately the same. The first three parts are used in training. Based on KFold cross validation, they are used in training three times. Each time, two of them are a training set and the rest are a validation set. The last part is used as a test set. As a result, in each training, three test results are generated, and the final result of this training is the average of the three.

The training is based on a pretrained ResNeXt50(32×4d) [13] model with a dense layer shown in Fig. 1. Four experiments are designed to find out whether the weighting method is a key factor in brain tumor detection and to compare the performance of the model on the original dataset and on the dataset provided with information on weighting methods. They are conducted over seeds 31, 37, 41, 42, 43, 47, 53, and epochs 10 to 60. So, for each epoch, there are 7 test results. The final test result is the average of them.

Single Label. In the original csv file, each image is labeled by whether there is a brain tumor in the MRI.

Separate Dataset to T1 and T2. To make sure that weighting methods do make a difference, the dataset is categorized into T1 and T2. To be more precise, the separation is based on the color of the cerebrospinal fluid, so T1, T1ce, and Flair are in the same

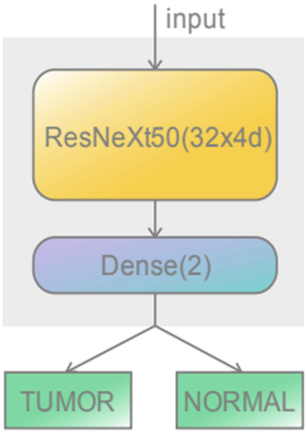


Fig. 1. Model

Table 1. Number of MRI images in each class

	Tumor	Normal
T1	99	55
T2	42	31

class, briefly denoted as T1, and T2 alone in another class. However, the T1 set is almost twice as large as the T2 set (as shown in Table 1). Since it is not reasonable to compare performance on two datasets with different sizes, after dividing into a training set and a testing set, each set is augmented in reasonable ways, so that their size is the same as the origin dataset. Reasonable augmentation methods are flipping and rotating. In most cases, brain MRI images are not upside down or displayed vertically, so only horizontal flip and small angle rotation (most are within ten degrees) are applied to these MRI images.

Two Label. These MRI images are labeled by tumor existence (tumor label) and weighting methods (weight label). Different from training the model over these two labels one by one, in this paper, they are trained at the same time, usually called multi-label training.

Random Label. This experiment is designed to ensure that the difference in the model performance is caused by the introduced weighting methods, which is the prior knowledge, rather than brought about by the label itself. As a result, the training is on a dataset in which one of its labels is randomized.

3.3 Experiment Results and Analysis

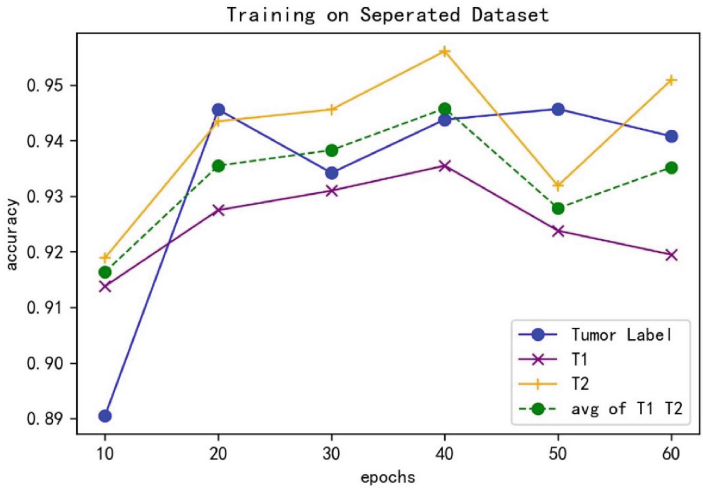
The model is implemented using pytorch. Table 2 shows the test scores of the proposed four experiments. In brief, there are two tasks. One task (TASK 1) is to classify brain MRI images into two classes, TUMOR and NORMAL. Another (TASK 2) is to tell

Table 2. Experiment results

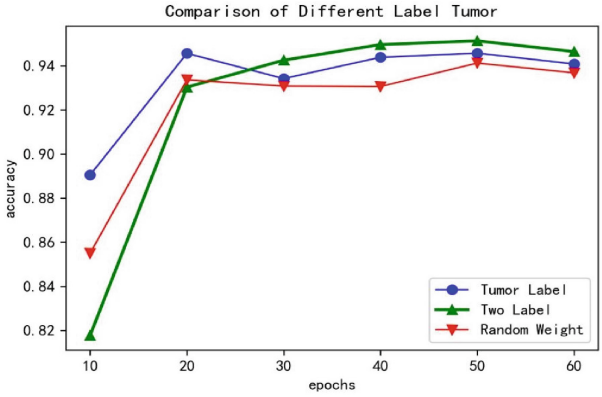
Epochs		10	20	30	40	50	60
Tumor label		0.8905	0.9456	0.9342	0.9438	0.9457	0.9408
Weight label		0.9611	0.9875	0.9773	0.9806	0.9837	0.9827
T1		0.9138	0.9275	0.9310	0.9355	0.9238	0.9195
T2		0.9189	0.9435	0.9456	0.9561	0.9319	0.9509
Two label	Tumor label	0.8178	0.9303	0.9425	0.9496	0.9513	0.9464
	Weight label	0.8946	0.9760	0.9829	0.9935	0.9893	0.9900
Random tumor	Tumor label	0.5671	0.4298	0.3936	0.4047	0.4072	0.4038
	Weight label	0.9456	0.9833	0.9838	0.9802	0.9856	0.9909
Random weight	Tumor label	0.8550	0.9336	0.9308	0.9306	0.9412	0.9368
	Weight label	0.4856	0.5404	0.4869	0.4973	0.4785	0.4763

whether the color of cerebrospinal fluid in brain MRI images is black or white, which is much simpler. In this table, Tumor Label is for the first task. T1 and T2 are also designed for the first task, but on modified datasets, the color of cerebrospinal fluid in brain MRI images is the same. Weight Label is for the second task. Two Label performs both tasks simultaneously. Random Tumor and Random Weight are designed for both tasks, and are trained with randomized labels of weighting methods and tumor labels, respectively.

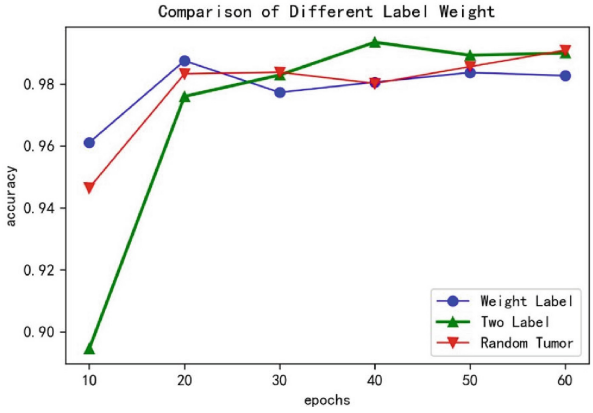
Figure 2(a) shows signs that with a dataset separated by the color of cerebrospinal fluid, it is plausible to speculate that TASK 1 is related to TASK 2. Figure 2(b) indicates that TASK 2 is conductive to TASK 1. After training for 30 epochs, the test score of Two Label is better than the one of Tumor Label by about 0.63%. Additionally, randomized Weight Labels do disturb the training process, reducing the test score by about 0.62%. Figure 2(c) illustrates that TASK 1 in turn affects TASK 2. After training for 30 epochs, the test score of Two Label is better than the one of Weight Label by about 0.78%.



(a) Training on separated dataset



(b) Comparison of different label tumor



(c) Comparison of different label weight

Fig. 2. Graph of Experiment Results

4 Discussion

In this paper, a series of experiments were conducted to prove that the proposed method is beneficial to training in the detection of brain tumors in MRI images. Also, this method is interpretable. If task A is the foundation of task B, then task B will be done better after finishing task A. To be more specific, to classify animal images by their species, it is easier to categorize them by their genes first. Additionally, when people learn something at the same time, if these things are strongly related, they will learn well. When it comes to the brain tumor detection on MRI images, with prior knowledge such as the weighting method in training, the accuracy of the test is enhanced. It should also be noted that the proposed method needs more training time. At the very beginning of the training, the performance of the method is inferior to the original one, which is quite reasonable since it needs time to discover relations between the color of cerebrospinal fluid and the existence of brain tumors.

5 Conclusion

An interpretable method of introducing prior knowledge to the detection of brain tumors in MRI images is proposed in this paper. Experiments are conducted over 7 different seeds and 6 different epochs to prove the feasibility and merits of this method. Firstly, it is illustrated that weighting methods have to do with brain tumor detection. Secondly, the performance of this method is evaluated. An outstanding accuracy of 95.13% was achieved on the test dataset. Compared with the traditional training method, this method improves the performance by 0.83% in the best case. Experiment results indicate that prior knowledge enhances performance on brain tumor detection by about 0.5% overall. Thirdly, it is tested that this improvement is the result of the method in this paper, not being brought by the introduced label itself. The proposed method is useful and be of value for reference on brain tumor detection in MRI images. Brain tumor detection is a simpler task compared with brain tumor classification and brain tumor segmentation. The original task is a two-class classification, making it easier than other classification tasks such as CIFAR10 or ImageNet. Additionally, the dataset used in the experiments is small, containing fewer than 300 images. Other studies on brain tumor classification use larger datasets with over 3000 images. As a result, it is hard to compare and evaluate the proposed method. For further study, this method can be applied to more complicated tasks and larger datasets, such as classifying brain tumors or categorizing animal images by their species on datasets with over 10,000 images.

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