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Basic Research on Image Diagnosis of Trigeminal Neuralgia Using MRI Image and Deep Learning

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Abstract

The main cause of trigeminal neuralgia is thought to be compression of the trigeminal nerve origin or organic disease due to tortuous or vagal vessels around the trigeminal nerve, and imaging diagnosis by MRI or CT is important. However, the diagnosis of trigeminal neuralgia requires the judgment of a skilled neurosurgeon and is not easy for inexperienced physicians. Therefore, this study proposes an image diagnosis method using convolutional neural networks (CNN) as basic research for constructing an automatic image diagnosis method for trigeminal neuralgia. In this study, three sets of data (A set, B set, and C set) are created from MRI images of the left and right trigeminal nerve of 43 donors, and the performance evaluation of each model is compared using each data set. As a result, the VGG16 classification in the C set showed the highest accuracy. The new VGG19 in C set achieved Accuracy: 0.979, Precision: 0.983, Recall: 0.975, F1-score: 0.979, and auc: 0.991. It was shown to be the best performing model in terms of low misclassification and Grad-CAM results.

Keyword

Trigeminal neuralgia, AI image recognition, Deep Learning, Convolutional Neural Network

1. Introduce

Trigeminal neuralgia, a common form of facial pain, is unilateral (rarely bilateral) paroxysmal facial pain that occurs in the area innervated by the trigeminal nerve. The pain is limited to the area innervated by a branch of the trigeminal nerve, is elicited by non-nociceptive stimuli, and recurs over a short period of time [1]. The age distribution of typical trigeminal neuralgia ranges from young to elderly. Typical trigeminal neuralgia is thought to be caused by compression of the trigeminal nerve by surrounding blood vessels at the trigeminal nerve origin. Although imaging is effective in the diagnosis of typical trigeminal neuralgia, it is difficult to diagnose in remote areas and requires the experience of the physician. In addition, the use of AI image recognition technology in the medical field is currently attracting attention, and convolutional neural networks [2], which excel in image recognition, have been shown to be effective in many cases [3][4].

2. Purpose

Aiming to establish an automatic diagnosis method using AI, this study examines a diagnosis method using deep learning as a basic research.

3. Image Analysis Method

3.1 Data Set Creation

From the MRI images of the trigeminal nerve of 43 donors, a total of 240 data sets (A set) of trigeminal neuralgia and non-trigeminal neuralgia images were prepared. In addition, a data set of 960 images (B set) and a data set of 2400 images (C set) were prepared by expanding the A set by a factor of 4 and 10, respectively.

3.2 Classification and Evaluation Methods

CNNs are used to classify trigeminal images from three different datasets into two classes: negative or positive. In this study, we perform transfer learning with three general-purpose CNNs, VGG16, VGG19, and ResNet 50, and compare the results. We evaluate the results using test data from Accuracy, Precision, Recall, F1-score, and auc, considering the identification of positives to be important. At the same time, we visualize the basis of the CNN decisions using Grad-CAM [5] to show the transparency of the evaluation.

4. Result

Comparing the three CNN models on each dataset, the VGG model showed stable results, with the VGG model on the C set achieving Accuracy: 0.942, Precision: 0.958, Recall: 0.926, F1-score: 0.942, auc: 0.982. The results show that the basic performance of the CNN is good. These results indicate that a basic diagnostic method using CNNs has been established, and further performance improvement is expected for practical use.

5. VGG model proposal method

The VGG model showed stable performance, and the results for Resnet 50 indicate that increasing the number of convolutional layers creates a situation where learning does not converge (i.e., accuracy does not increase), so it is predicted that performance will not increase for multi-layer models compared to Resnet 50. Therefore, in order to propose a more accurate model, we focus on the structure of the VGG model and improve its structure. The first method is to change the discriminator of the VGG model to a support vector machine (SVM) [6], which is good at two-class classification and thus compatible with this study. Since we observed some learning variability during the training phase, we added Batch Normalization (BN)[7] to the layers of the VGG model as a second method to stabilize the overall network learning process and increase the learning speed.

5. Results of proposal methods

In the results of Support Vector Machine, the

performance of both VGG16 and VGG19 remained at 0.7~0.8 for all the evaluation indices, showing no performance improvement, but the addition of Batch Normalization improved the performance of VGG16. Table 1 shows the results of VGG16 after the addition of BN. The results showed an improvement of 1.3% in VGG after the addition of BN. Table 2 shows the results of VGG19 after the addition of BN. Similarly, the results for the C set show a significant performance improvement over the original model: Accuracy: 7.9%, Precision: 8.5%, Recall: 6.2%, F1-score: 7.3%, and auc: 2.7%, the best performance in this study, and the best performance in the Grad-CAM The Grad-CAM results (Figure 1) also show the reliability of the performance.

Tab1. Test result with VGG16 + BN

		Accuracy	Precision	Recall	F1-score	auc
VGG16 + BN	A set	0.792	0.800	0.727	0.762	0.944
	B set	0.917	0.880	0.957	0.917	0.963
	C set	0.954	0.944	0.967	0.955	0.995

Tab2. Test result with VGG19 + BN

		Accuracy	Precision	Recall	F1-score	auc
VGG19 + BN	Aset	0.792	0.714	0.909	0.800	0.888
	Bset	0.896	0.875	0.913	0.894	0.951
	Cset	0.979	0.983	0.975	0.979	0.991

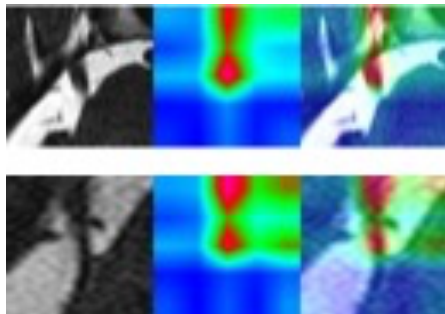


Fig1. Grad-CAM of VGG19 + BN on C set

6. Conclusion

In this research, we examine and propose an AI diagnostic method for image analysis of trigeminal neuralgia using deep learning. In doing so, we conducted a series of experiments with three types of CNN-based classification. We conducted a series of experiments with the models and compared the performance of each model. As a result, the best performing model was VGG16 in the C set, achieving accuracy: 0.942, precision: 0.958, recall: 0.926, F1-score: 0.942, auc: 0.982. To further improve the performance of the VGG model, we improved the structure of the VGG model and proposed two methods. The support vector machine did not improve the performance, but the addition of Batch Normalization did, VGG19 achieved accuracy of 0.979, precision: 0.983, recall: 0.975, F1-score: 0.979, and auc: 0.991 in the C set, and was the best performing model in

terms of few misclassifications and Grad-CAM results. The model also performed the best in terms of low misclassification and Grad-CAM results. Based on this high classification accuracy, we believe that this study will play a role in the development of an AI diagnostic system for imaging diagnosis of trigeminal neuralgia, which may be useful in the near future in regions where there are medical disparities. In this paper, we examine and propose an AI diagnostic method for image analysis of trigeminal neuralgia using deep learning. In doing so, we conducted a series of experiments with three types of CNN-based classification. We conducted a series of experiments with the models and compared the performance of each model. As a result, the best performing model was VGG16 in the C set, achieving accuracy: 0.942, precision: 0.958, recall: 0.926, F1-score: 0.942, auc: 0.982. To further improve the performance of the VGG model, we improved the structure of the VGG model and proposed two methods. The support vector machine did not improve the performance, but the addition of Batch Normalization did, VGG19 achieved accuracy of 0.979, precision: 0.983, recall: 0.975, F1-score: 0.979, and auc: 0.991 in the C set, and was the best performing model in terms of few misclassifications and Grad-CAM results. The model also performed the best in terms of low misclassification and Grad-CAM results. Based on this high classification accuracy, we believe that this study will play a role in the development of an AI diagnostic system for imaging diagnosis of trigeminal neuralgia, which may be useful in the near future in regions where there are medical disparities.

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