Convolutional Neural Networks For Automated Edema Segmentation in Patients With Intracerebral Hemorrhage

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Abstract

Intracerebral hemorrhage (ICH) is a common type of stroke with high morbidity and mortality rate. Edema often forms around ICH. Because edema increases the chance of poor outcome, edema quantification is needed for finding the optimal ICH treatment. CNN has been proven to be a reliable method in medical image segmentation. In this study, we introduce CNN to develop an automated method for edema and ICH quantification. We found that our CNN is a promising quantification method for edema.

1 Introduction

Intracerebral hemorrhage (ICH) is a common type of stroke caused by the rupture of an artery in the brain Sacco et al. [1], Fewel et al. [2]. It accounts for 10 to 15 % of all strokes and it has a high morbidity and mortality rate Fewel et al. [2]. Edema is a swelling of brain tissue caused by the accumulation of fluid. It is a major cause of poor outcome among patients with ICH and it develops rapidly during the first 72 hours Murthy et al. [3]. Multiple factors associated with ICH could provoke brain edema. Edema volume quantification after ICH can improve decision-making for treatment. The manual delineation of edema on CT is a difficult and time- consuming task, with considerable inter-observer variability Volbers et al. [4], Boers et al. [5]. An automatic algorithm for quantifying edema on a CT scan would be beneficial to decrease inter-observer variances and improve quantification of edema. In this study, we use convolutional neural networks (CNNs) to create an automated edema and ICH quantification method. CNN is a machine learning method that uses small learnable convolutional filters for voxel classification.

ICH segmentation methods based on Hounsfield unit thresholding have already been introduced in the literature Volbers et al. [4], Boers et al. [5]. However, CT scans vary in intensity, making it hard to set one threshold for all scans. CNNs take into account the neighboring voxels for classification, which can be an advantage due to the contrast between ICH, edema and brain regions. Previous studies have shown the effectiveness of CNNs in medical image segmentation Barros et al. [6]. The aim of this study is to develop an automated ICH and edema segmentation method using CNNs and non-contrast CT scans. The model was trained and tested on CT scans obtained from the PATCH study (24). This study investigated the effect of platelet transfusion in ICH patients.

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ICH on non contrast CT scans. The model was trained and tested on CT scans obtained from the PATCH study de Gans et al. [7]. This study investigated the effect of platelet transfusion in ICH patients.

2 Methods

We included 154 patients from the image dataset of the PATCH study de Gans et al. [7]. This dataset included CT images of 190 patients taken during admission (and after 24 hours) of patients with ICH. Patients with a Glasgow Coma Scale between 8 and 15 were included. Patients were excluded when the amount of intraventricular blood was more than a sedimentation in the posterior horns of the lateral ventricles or if the present hematoma suggested epidural, subdural, aneurysmal, or arteriovenous malformation. We also excluded scans with large artifacts. A total of 241 scans from 154 patients were included in our study. The ICH and edema volume of each scan was manually segmented by a trained neurologist. The CNN models were trained on 80% of the data and validated on the remainder 20%.

In our approach patches were extracted for voxels inside the brain region (after removing the skull from the scans). It is important to keep the balance between classes during training to prevent the network from learning to classify only one class. Since brain tissue was the most common class, patches from ICH and edema were augmented by flipping along the sagittal plane because they emulate biologically plausible variations due to brain symmetry. Patches from brain tissue were randomly selected until the total number of brain patches was the same of ICH and edema. All patches were labeled corresponding to the classification of the center voxel.

Earlier research has shown state-of-the-art results with a CNN architecture for subarachnoid hemorrhage segmentation Barros et al. [6]. Because of the similar features of edema and the use of ICH segmentation in our study, we used the same architecture with two different sizes of patch for fine tuning. This architecture takes patches of size [19x19] and [17x17] as input and is composed of two convolutional layers with [5x5x128] and [5x5x256] filters. Zero padding and bias were introduced for every convolutional operation. ReLU Nair and Hinton [8] was used as activation function. A [2x2] MaxPooling layer was added after every convolutional layer. The fully connected layer was composed of 256 nodes. The edema segmentations resulting from the CNN were post-processed by removing small particles and regions that were not around ICH, since edema always surrounds ICH. To evaluate the segmentation accuracy, the Dice score was computed for ICH and edema segmentation.

3 Results

Table 1 presents the Dice scores for ICH and edema segmentations obtained with the trained models and the testing set. The best Dice score for ICH was obtained with setup A, 0.74 ± 0.14. The best Dice scores for edema segmentation was 0.44 ± 0.17.

Training for more iterations did not improve results, since the Dice score for 200 epochs was not better than for 100 epochs. Figure 1 presents an example of edema segmentation before and after post-processing the CNN's output.

Table 1: Performance of CNN models on the testing set for segmenting ICH and edema.

Training code	Patch size	Number of epochs	Dice ICH	Dice edema
A	19 x 19	100	0.74 ± 0.14	0.44 ± 0.17
B	19 x 19	200	0.73 ± 0.16	0.43 ± 0.17
C	17 x 17	100	0.71 ± 0.15	0.41 ± 0.16
D	17 x 17	200	0.71 ± 0.17	0.41 ± 0.18

4 Discussion

In this study, the best model for training CNN on edema classification achieved an average Dice score of 0.44. Our model performs moderately as quantification method. This suggests that, although we have not found perfect results, CNNs are promising for edema segmentation.

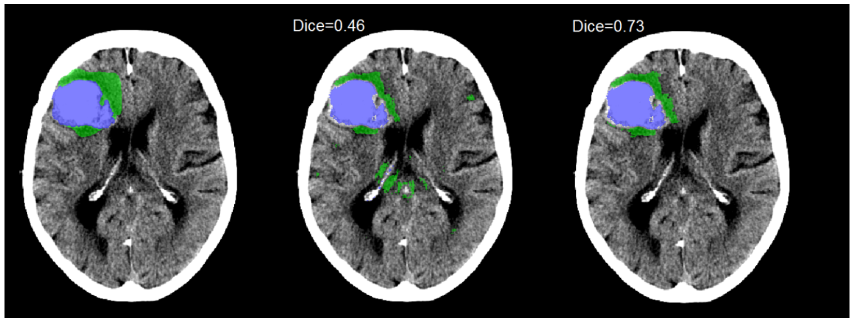

Figure 1: Example of edema (green) and ICH (blue) segmentation. Ground truth (left), CNN segmentation (middle) and segmentation after post-processing (right).

The accuracy for different patch sizes did not differ greatly. Further research should be done to test performances of CNNs with a bigger range of patch sizes. We used a manual segmentation as gold standard for our study. Since edema segmentation is a challenging task, manual segmentations are never perfect, which might reduce the accuracy of the trained models.

We found that our CNN performed well for ICH segmentation. This could be because our CNN architecture was initially created for subarachnoid hemorrhage segmentation. Furthermore, there is a large contrast between the intensity of ICH voxels and brain voxels, which makes it easier to segment ICH. Brain voxels with similar HU values as edema were often categorized as edema by the trained CNN. Although we solved this issue with post-processing, further improvements are still needed.

5 Conclusion

In this study, we provided a promising automatic edema segmentation method using CNNs. Further research should be done for improving this automatic edema segmentation method.

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