Classification and Segmentation of Intracranial Hemorrhage Using CT Scans

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Abstract

Automatic detection, subtyping, and segmentation of brain hemorrhages on CT scans can serve as a useful clinical screening tool to support radiological interpretation and clinical decision-making, especially in trauma settings. To facilitate the development of such algorithms, the Radiological Society of North America (RSNA) released a publicly available dataset containing more than 25,000 CT scans in 2019. Since then, numerous groups have leveraged this dataset to train machine learning models to detect, classify, or segment brain hemorrhages. However, no model had performed classification and segmentation simultaneously. To fill this gap, this project will develop a multitask deep learning model based on 222 CT scans retrieved from the RSNA dataset. We will evaluate and optimize the model for concurrent classification and segmentation, with the goal of improving the efficiency and accuracy of radiological interpretation of CT scans of two different types of brain hemorrhages: intraparenchymal (IPH) and intraventricular (IVH).

1 Introduction

Computerized Tomography (CT) is a key and common diagnostic technique widely used in medical imaging, particularly to clinically confirm intracranial hemorrhages in the initial diagnostic phase for patients who present with head trauma, stroke symptoms, or signs of increased intracranial pressure. Brain hemorrhages are conditions in which early detection, subtype classification, and segmentation are essential for patient survival and long-term health outcomes. In addition, accurate and rapid interpretation of these scans is necessary for timely medical decision-making, particularly in stroke evaluation and trauma care settings.

Automated classification and segmentation of intracranial hemorrhages using machine learning can significantly improve the efficiency of CT scan interpretation. This can help streamline workflow by automating the initial screening and triage process, reducing the time to diagnosis, and expediting treatment. Such algorithms will be particularly valuable in high-volume trauma centers and remote locations where immediate radiologist interpretation may not be available. The proposed trained algorithms aim to detect and segment two types of intracranial hemorrhages: intraparenchymal (IPH) and intraventricular (IVH).

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2 Related Works

As mentioned, since intracranial hemorrhage is such a life-threatening condition that requires rapid and accurate treatment, identifying the locations of intracranial hemorrhage and classifying their subtypes become an urgent issue. In the past decade, a lot of effort has been put into performing these tasks. More specifically, many studies employ CT which is simply in terms of operation and readily available. However, performing hemorrhage segmentation and classification in CT scans remains challenging due to the low signal-to-noise ratio, low contrast, and other associated image artifacts due to inconsistency in the acquisition of the scans. In addition, small abnormalities of around 100 pixels need to be detected with high accuracy. Therefore, these processes usually involve the input of experts with years of training. In particular, the Radiological Society of North America (RSNA) presented a challenge in 2019, gathering radiologists and researchers of artificial intelligence (AI), and aiming to improve the segmentation and classification of intracranial hemorrhage. Since then, lots of method that employed machine learning algorithms to accomplish these tasks have been proposed.

In terms of hemorrhage segmentation, the U-Net model is one of the most popular methods. Hssayeni et al. employed a standard U-Net model on a small dataset which only contains 82 CT scans [1]. In order to solve the class imbalance problem in the dataset, Patel et al. also included a weighted map in their U-Net segmentation training [2]. More recently, Khan MM et al. also demonstrated the use of a U-Net model with DenseNet201 pre-trained encoder in performing 3D segmentation [3]. In terms of hemorrhage subtype classification, Ye H et al. applied convolutional and recurrent neural network (CNN-RNN) for distinguishing the 5 subtypes of hemorrhage [4]. Burduja M et al. combined CNN and a Long Short-Term Memory (LSTM) network to perform subtype classification [5]. However, models that can comprehensively perform both hemorrhage segmentation and subtype classification in the same model remain mostly lacking.

3 Methods and Algorithms

3.1 Data Collection & Preprocessing

We will use the data originating from the RSNA dataset [6] and HemSeg-200 [7]. The dataset consists of 222 CT volumes, with 114 volumes diagnosed with intraparenchymal hemorrhage (IPH) and 108 volumes identified as intraventricular hemorrhage (IVH) [7]. Each scan has the spatial resolution of 512×512 with an inconsistent number of slices from 24 to 56 (mean 33 slices). A comprehensive preprocessing pipeline proposed in nnU-Net [8] framework including image resampling, intensity normalization and other steps will be modified and applied to achieve good data initialization.

3.2 Network Architecture

To achieve the goal of segmentation and classification of intracranial hemorrhage on CT scans, we propose a multitask deep learning approach for improving the accuracy and inference efficiency. This approach utilizes a framework containing a segmentation and classification module. Each module adopts the auto-encoder architecture [9] and share the information of encoder. The encoder compresses high-dimensional data, such as a 3D CT volume, into low-dimensional latent vectors, and the decoder then reconstructs the spatial information from these latent representations, ultimately generating voxel-wise probability maps for segmentation and categorical probabilities for the classification task.

3.3 Evaluation Metrics

To assess the performance of the multitask learning framework for classification and segmentation, we employ a set of quantitative evaluation metrics tailored to each task. For segmentation performance, we utilize voxel-wise evaluation metrics like Dice Similarity Coefficient (DSC), Intersection of Union (IoU) and Hausdorff Distance (HD) that measure the accuracy of the predicted segmentation masks against ground truth labels, while for classification, we employ standard metrics that evaluate the accuracy of categorical predictions such as Accuracy, Precision, Recall, and F1-Score.

References

[1] M. D. Hssayeni, M. S. Croock, A. D. Salman, H. F. Al-Khafaji, Z. A. Yahya, and B. Ghoraani, "Intracranial hemorrhage segmentation using a deep convolutional model," *Data*, vol. 5, no. 1, p. 14, 2020.

[2] A. Patel, F. H. Schreuder, C. J. Klijn, M. Prokop, B. v. Ginneken, H. A. Marquering, Y. B. Roos, M. I. Baharoglu, F. J. Meijer, and R. Manniesing, "Intracerebral haemorrhage segmentation in non-contrast ct," *Scientific reports*, vol. 9, no. 1, p. 17858, 2019.

[3] M. M. Khan, M. E. Chowdhury, A. S. Arefin, K. K. Podder, M. S. A. Hossain, A. Alqahtani, M. Murugappan, A. Khandakar, A. Mushtak, and M. Nahiduzzaman, "A deep learning-based automatic segmentation and 3d visualization technique for intracranial hemorrhage detection using computed tomography images," *Diagnostics*, vol. 13, no. 15, p. 2537, 2023.

[4] H. Ye, F. Gao, Y. Yin, D. Guo, P. Zhao, Y. Lu, X. Wang, J. Bai, K. Cao, Q. Song *et al.*, "Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network," *European radiology*, vol. 29, pp. 6191–6201, 2019.

[5] M. Burduja, R. T. Ionescu, and N. Verga, "Accurate and efficient intracranial hemorrhage detection and subtype classification in 3d ct scans with convolutional and long short-term memory neural networks," *Sensors*, vol. 20, no. 19, p. 5611, 2020.

[6] A. E. Flanders, L. M. Prevedello, G. Shih, S. S. Halabi, J. Kalpathy-Cramer, R. Ball, J. T. Mongan, A. Stein, F. C. Kitamura, M. P. Lungren *et al.*, "Construction of a machine learning dataset through collaboration: the rsna 2019 brain ct hemorrhage challenge," *Radiology: Artificial Intelligence*, vol. 2, no. 3, p. e190211, 2020.

[7] C. Song, Q. Zhao, J. Li, X. Yue, R. Gao, Z. Wang, A. Gao, and G. Fu, "Hemseg-200: A voxel-annotated dataset for intracerebral hemorrhages segmentation in brain ct scans," *arXiv preprint arXiv:2405.14559*, 2024.

[8] F. Isensee, P. F. Jaeger, S. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnu-net: a self-configuring method for deep learning-based biomedical image segmentation," *Nature methods*, vol. 18, no. 2, pp. 203–211, 2021.

[9] D. Bank, N. Koenigstein, and R. Giryes, "Autoencoders," *Machine learning for data science handbook: data mining and knowledge discovery handbook*, pp. 353–374, 2023.