ORIGINAL RESEARCH ARTICLE

Automatic segmentation of intracranial hemorrhage using coarse and fine deep learning models

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ABSTRACT

To save patients' lives, it is important to go for an early diagnosis of intracranial hemorrhage (ICH). For diagnosing ICH, the widely used method is non-contrast computed tomography (NCCT). It has fast acquisition and availability in medical emergency facilities. To predict hematoma progression and mortality, it is important to estimate the volume of intracranial hemorrhage. Radiologists can manually delineate the ICH region to estimate the hematoma volume. This process takes time and undergoes inter-rater variability. In this research paper, we develop and discuss a fine segmentation model and a coarse model for intracranial hemorrhage segmentations. Basically, two different models are discussed for intracranial hemorrhage segmentation. We trained a 2DDensNet in the first model for coarse segmentation and cascaded the coarse segmentation mask output in the fine segmentation model along with input training samples. A nnUNet model is trained in the second fine stage and will use the segmentation labels of the coarse model with true labels for intracranial hemorrhage segmentation. An optimal performance for intracranial hemorrhage segmentation solution is obtained.

Keywords: coarse; segmentation; artery segmentation; nnUNet; deep learning

1. Introduction

Among the different stroke types, intracranial hemorrhage (ICH) is one of the stroke types considered to have high mortality[1]. It's better to go for early diagnosis at an early stage to save patients' lives. In common practice, for diagnosing intracranial hemorrhage, non-contrast computed tomography (NCCT) is commonly used. In most of the medical emergency departments, it is easily available[2]. Accurate ICH volume estimation is significantly important for predicting hematoma premature mortality and development in normal clinical diagnosis procedures[3]. The radiologists identify the ICH region and manually delineate it to estimate hematoma volume. It is not only a time-consuming process but also agonizes from inter-rater variability. Clinically, the most widely used method is called the ABC/2 method[3], which is used to estimate hemorrhage volume. However, this method produced a higher volume estimation error. A fully automated segmentation method that would be more accurate and rapid in estimating the volume of the intracranial hemorrhage is developed to overcome the drawbacks mentioned earlier. Accurate segmentation of ICH is challenging due to blurred boundaries and large variations in shapes and locations. A segmentation model

based on deep learning has been commonly used in medical image segmentation tasks[4] and could provide accurate segmentation of ICH. Organ segmentation is one of the most fundamental image analysis tasks to support the above clinical applications. To be deployed in clinical practice, a segmentation method should be robust to the testing cases from different medical centers and achieve clinically acceptable accuracy. Moreover, efficiency is also an important factor during the deployment[5]. A key factor for assessing the state of the heart after myocardial infarction (MI) is to measure whether the myocardium segment is viable after reperfusion or revascularization therapy. Delayed enhancement-MRI or DE-MRI, which is performed 10 min after injection of the contrast agent, provides high contrast between viable and nonviable myocardium and is therefore a method of choice to evaluate the extent of MI[6]. Deep learning is used for feature extraction and encompasses the application of different models, such as fine-tuned Inception-v3 and fine-tuned Xception. The classification of brain tumors is explored through deep- and machine-learning algorithms including softmax, Random Forest, Support Vector Machine, K-Nearest Neighbors, and the ensemble technique[7]. Machine learning (ML) and ensemble approaches have been used to construct a framework to automatically classify patients according to their clinical conditions. 10-fold cross-validation is used during the model's training to avoid overfitting. Approaches such as Stratified, Over-sampling, Under-sampling, NearMiss, and SMOTE were tested in order to address the imbalance of the data (i.e., the proportion of cases per pathology). The ground truth is provided by a DE-MRI exam (normal exam, myocarditis, or myocardial infarction)[8]. Fetoscopic laser photocoagulation of placental anastomoses is the most effective treatment for twin-to-twin transfusion syndrome (TTTS). A robust mosaic of the placenta and its vascular network could support surgeons' exploration of the placenta by enlarging the fetoscope field-of-view. In this work, we propose a learning-based framework for field-of-view expansion from intra-operative video frames[9]. nnUNet for fine segmentation can be used[10].

A novel SLice EXpansion Network (SLEX-Net), incorporated hematoma expansion in the segmentation architecture by directly modeling the hematoma variation among adjacent slices. Firstly, a new module named Slice Expansion Module (SEM) was built, which can effectively transfer contextual information between two adjacent slices by mapping predictions from one slice to another. Secondly, to perceive contextual information from both upper and lower slices, we designed two information transmission paths: forward and backward slice expansion, and aggregated results from those paths with a novel weighing strategy. By further exploiting intra-slice and inter-slice context with the information paths, the network significantly improved the accuracy and continuity of segmentation results[11]. A novel automatic segmentation method for accurate intracranial hemorrhage segmentations on NCCT images is proposed. However, there are no such challenges available right now. Thus, we intend to host the first intracranial hemorrhage segmentation challenge on non-contrast head CT (named INSTANCE 2022)[12], which will serve as a solid benchmark for intracranial hemorrhage segmentation tasks. In this paper, to tackle errors that happen in manual segmentation, the following findings are discussed:

1) Developed 2DDensNet model for coarse segmentation to get a 3D prediction.
2) Use nnUNet for fine segmentation.
3) The proposed 2DDensNet was used for coarse segmentation and concatenated the output of coarse segmentation with fine nnUNet segmentation to get the final segmentation output.

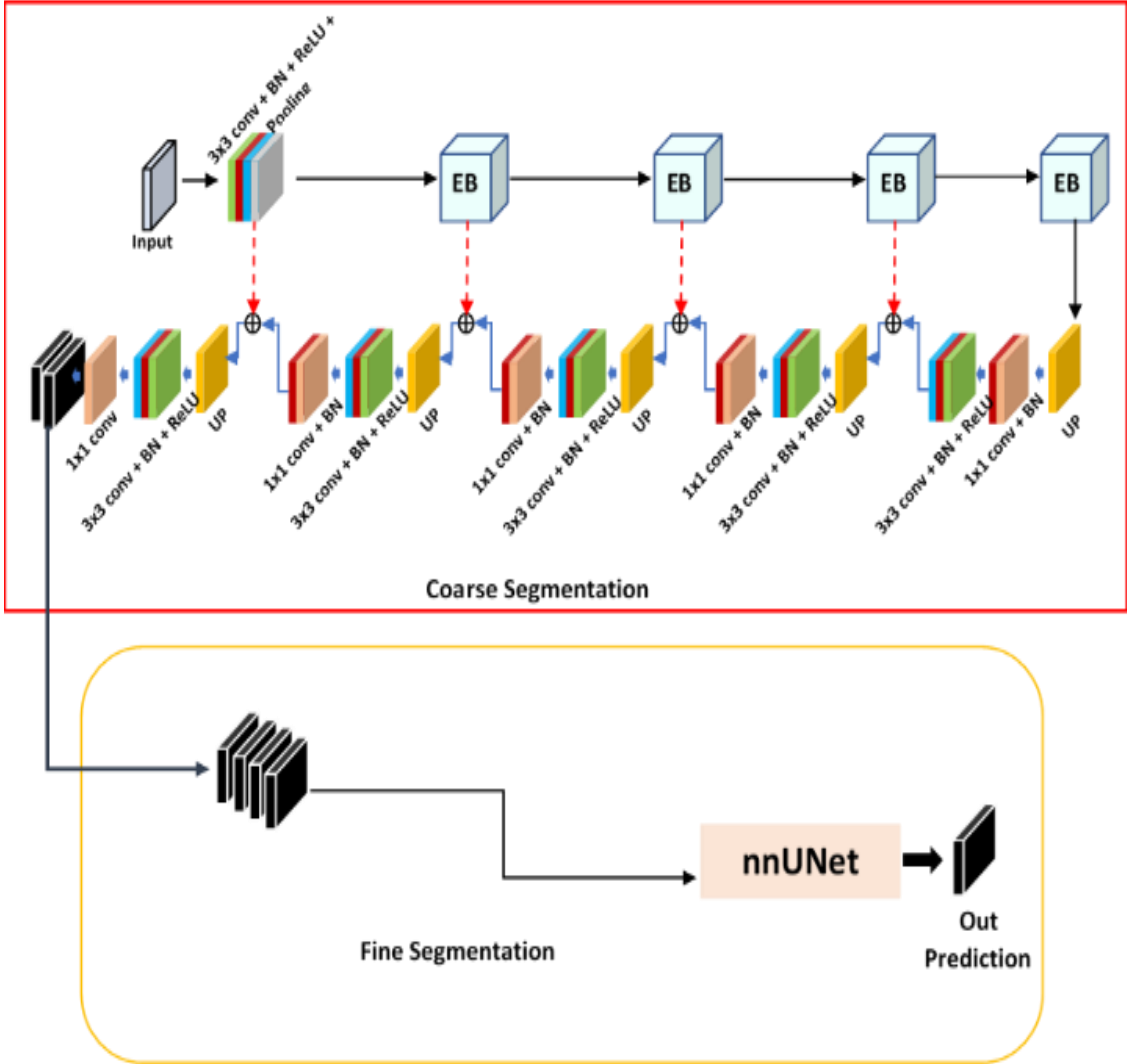A complete description of the proposed model is shown in **Figure 1**.

Figure 1. Intracranial hemorrhage segmentation challenge on non-contrast head CT (NCCT).

2. Material and methods

2.1. Dataset

For our research purpose, we collected 200 non-contrast head CT volumes of clinically diagnosed patients that contain various kinds of ICH, including subdural hemorrhage, epidural hemorrhage, intraventricular hemorrhage, intraparenchymal hemorrhage, and subarachnoid hemorrhage. From Peking University Shougang Hospital, China, the CT volumes were obtained. 10 radiologists with more than 5 years of clinical experience were used to label the data. The CT volume size is taken as $512 \times 512 \times N$; the value for N lies in [20, 70]. The CT volume pixel spacing is 0.42 mm $\times$ 0.42 mm $\times$ 5 mm. NIFTI files are used to store the images. The annotations for Voxel-level segmentation are: 0—background; 1—ICH.

2.2. Proposed method (coarse segmentation model)

A dense encoder followed by a non-dense decoder is used to propose the model for coarse segmentation. To enable the flow of information and gradients throughout the network, a dense encoder is used. This can also be used for facilitating training convergence. Five dense blocks, each consisting of six dense layers followed by a transition layer, are used in the dense encoder. Two convolutional layers with batch normalization (BN) and ReLU activation functions are used in each dense layer. A 1×1 kernel is used in the first convolutional layer, and a 3×3 kernel is used in the second. All the transition layers have a BN layer, a

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1×1 convolutional layer, and a 2×2 average pooling layer. Feature-map size can be reduced by the transition layer. The increasing number of feature maps at each encoder stage can be found in the dense block. 5-fold cross-validation is used to train the model. 2D images are stacked to make a 3D segmentation mask to compute the final prediction. The predicted segmentation mask is further cascaded in a fine segmentation model. **Figure 1** shows the proposed 2D DenseNet model. **Figure 2** shows the dense block used in the encoder side of the proposed model.
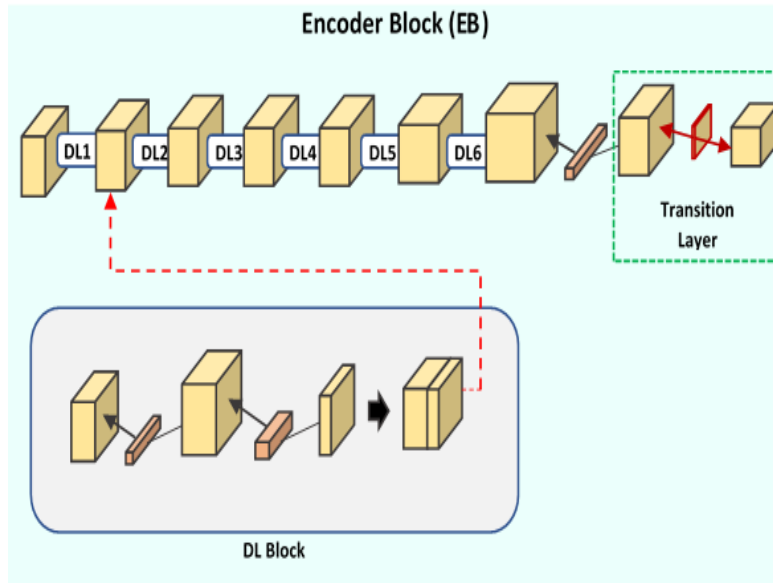

Figure 2. Proposed DensNet blocks (DL: Dense layer).

2.3. Fine segmentation model

A nnUNet with fivefold cross-validation is used to select the best fold for intracranial hemorrhage segmentation, training, and optimization parameters are modified and compared to the original nnUNet. $128 \times 128 \times 128$ using 500 epochs is the patch size in nnUNet.

2.4. Training and optimization details

For pre-processing and analysis of the datasets, PyTorch deep learning model and other libraries based on Python are used. For reading and writing the nifty data volume SimpleITK is used. The learning rate of 0.0004 with Adam optimizer is implemented for training the proposed model. To define the loss function between the output of the model and the ground-truth sample, a binary cross-entropy is adopted. Two batch sizes with 200 epochs have been used with 20 early stopping steps. For prediction in the validation phase, the best model weights have been saved. The $256 \times 256 \times 16$ input image size was used for training the proposed model. For training, model development, optimization, and testing Pytorch are used. Also, a V100 tesla NVidia-GPU machine is used for testing and training the proposed model. 18 h is the total training time that uses a single GPU V100 tesla machine. To augment the dataset for training the proposed model, data augmentation methods such as HorizontalFlip ($p = 0.5$), VerticalFlip ($p = 0.5$), and RandomGamma ($p = 0.8$) were used. The dataset cases consist of different intensity ranges and are normalized between 0 and 1 using the max and min intensity normalization methods. Using the linear interpolation method, the training shape of each volume is fixed at ($256 \times 256 \times 16$) and can be used to resample the prediction mask to the original shape for each validation volume. The proposed model has been resampled in such a way that it has the same size and spacing compared to the original image and copies all the meta-data, referring to the origin, direction, orientation, etc.

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3. Results and discussion

The results of validation and test datasets are shown in **Table 1**. To test the proposed model, 30 volumes have been used for validation, and 70 volumes were used to test the proposed model. Three important parameters are considered to validate the result. Dice coefficient, normalized surface distance, and average volume distance are the important coefficients considered for validation and to test the data set. The values obtained are clearly mentioned in **Table 1**. We achieved 0.699 Dice Score on validation and 0.650 on the test dataset, respectively. Also, we achieved 0.487 on normalized surface distance on validation and 0.339 on the test data set. The average volume difference values are 0.259 from validation and 0.459 from the test data set. Both the DC and NSD values are slightly higher than the test dataset. The RVD value is a bit lower than the test dataset.

Table 1. DC (Dice coefficients), NSD (normalized surface distance), and RVD (average volume difference) performance metrics using the proposed validation and test dataset.

Models	Dataset	DC	NSD	RVD
Proposed model	Validation	0.699	0.487	0.259
Proposed model	Test	0.650	0.339	0.469

Figure 3 shows the open test cases for four different subjects for qualitative analysis of prediction. The first two columns show the 2D slices and the third column shows the 3D volume visualization. We produced a better visualization of the predicted mask. As shown in **Figure 3**, this model reconstructs segmentation, especially in the tumor region.
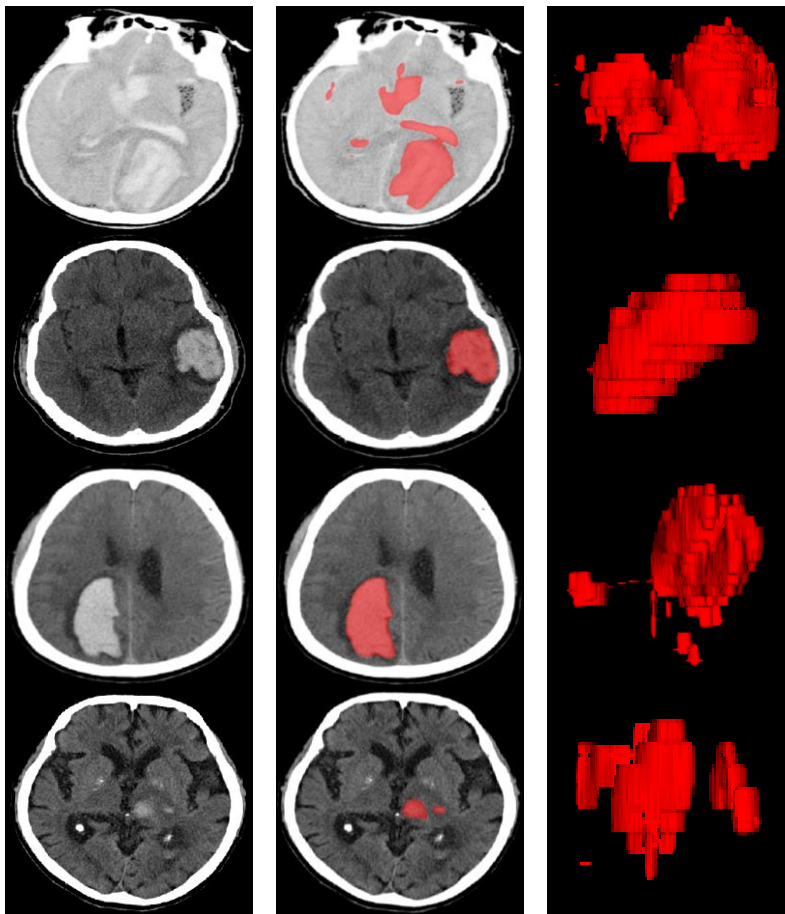

Figure 3. Open test cases (subject_1, subject_2, subject_3, subject_4) for qualitative analysis of prediction.

4. Conclusion

A coarse and fine segmentation model for intracranial hemorrhage segmentations is developed and discussed in this paper. Two different models for intracranial hemorrhage segmentations are trained to validate the solution. 2DDensNet is used in coarse segmentation, and nnUNet has been applied in fine segmentation. To further enhance the performance of ICH segmentation in the future, we will explore other 3D single segmentation methods.

Author contributions

Conceptualization, AQ and MM (Moona Mazher); methodology, AQ; software, MKAAK; validation, RUM, AQ and MKAAK; formal analysis, MM (Mastaneh Mokayef); investigation, CKA; resources, LWH; data curation, LWH; writing—original draft preparation, MKAAK; writing—review and editing, MKAAK; visualization, CKA; supervision, AQ; project administration, AQ; funding acquisition, AQ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflicts of interest associated with this research study. The research was conducted in an unbiased manner, and there are no financial, personal, or professional relationships that could potentially influence the results or interpretation of the findings. This statement is provided to ensure transparency and maintain the integrity of the research presented in this journal submission.

References

1. Van Asch CJJ, Luitse MJA, Rinkel GJE, et al. Incidence, case fatality, and functional outcome of intracerebral haemorrhage over time, according to age, sex, and ethnic origin: A systematic review and meta-analysis. *The Lancet Neurology* 2010; 9(2): 167–176. doi: 10.1016/S1474-4422(09)70340-0
2. Goldstein JN, Gilson AJ. Critical care management of acute intracerebral hemorrhage. *Current Treatment Options in Neurology* 2011; 13: 204–216. doi: 10.1007/s11940-010-0109-2
3. Kothari RU, Brott T, Broderick JP, et al. The ABCs of measuring intracerebral hemorrhage volumes. *Stroke* 1996; 27(8): 1304–1305. doi: 10.1161/01.STR.27.8.1304
4. Payette K, Li HB, de Dumast P, et al. Fetal brain tissue annotation and segmentation challenge results. *Medical Image Analysis* 2023; 88: 102833. doi: 10.1016/j.media.2023.102833
5. Ma J, Zhang Y, Gu S, et al. Fast and low-GPU-memory abdomen CT organ segmentation: The flare challenge. *Medical Image Analysis* 2022; 82: 102616. doi: 10.1016/j.media.2022.102616
6. Lalande A, Chen Z, Pommier T, et al. Deep learning methods for automatic evaluation of delayed enhancement-MRI. The results of the EMIDEC challenge. *Medical Image Analysis* 2022; 79: 102428. doi: 10.1016/j.media.2022.102428
7. Noreen N, Palaniappan S, Qayyum A, et al. Brain tumor classification based on fine-tuned models and the ensemble method. *Computers, Materials & Continua* 2021; 67(3): 3967–3982. doi: 10.32604/cmc.2021.014158
8. Chen Z, Lalande A, Salomon M, et al. Automatic deep learning-based myocardial infarction segmentation from delayed enhancement MRI. *Computerized Medical Imaging and Graphics* 2022; 95: 102014. doi: 10.1016/j.compmedimag.2021.102014
9. Bano S, Vasconcelos F, Stoyanov D. FetReg2021: A challenge on placental vessel segmentation and registration in fetoscopy. Available online: https://discovery.ucl.ac.uk/id/eprint/10157782/ (accessed on 25 October 2023)
10. Isensee F, Jaeger PF, Kohl SAA, et al. nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation. *Nature Methods* 2021; 18(2): 203–211. doi: 10.1038/s41592-020-01008-z

11. Li X, Luo G, Wang W, et al. Hematoma expansion context guided intracranial hemorrhage segmentation and uncertainty estimation. *IEEE Journal of Biomedical and Health Informatics* 2021; 26(3): 1140–1151. doi: 10.1109/JBHI.2021.3103850

12. Li X, Wang K, Liu J, et al. The 2022 intracranial hemorrhage segmentation challenge on non-contrast head CT (NCCT). Available online: https://zenodo.org/records/6362221 (accessed on 25 October 2023).