Automatic Segmentation of Intracranial hemorrhage using Coarse and Fine deep learning models

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Abstract. Early and accurate diagnosis of Intracranial hemorrhage (ICH) is critical for saving patients' lives. In regular clinical practice, Non-Contrast Computed Tomography (NCCT) is the most widely used modality for diagnosing ICH due to its fast acquisition and availability in most emergency departments. In clinical diagnosis procedures, accurately estimating the volume of intracranial hemorrhage is significant for predicting hematoma progression and early mortality. The hematoma volume can be estimated by manually delineating the ICH region by radiologists, which is time-consuming and suffers from inter-rater variability.
In this paper, we have developed a coarse and fine segmentation model for intracranial hemorrhage segmentations. We have trained two different models for intracranial hemorrhage segmentations. In the first model, we have trained 2DDensNet for coarse segmentation and cascaded the coarse segmentation masks output in the fine segmentation model along with input training samples. In the fine stage, we have trained the nnUNet model that will use the segmentation labels of the coarse model with true labels for Intracranial hemorrhage segmentation. The proposed solution provides optimal performance for Intracranial hemorrhage segmentation.

Keywords: Coarse and Fine Segmentation, Pulmonary Artery segmentation, nnUNet, DesnUNet.

The main findings of this paper are as follows:

1. Developed 2DDensNet model for coarse segmentation to get a 3D prediction

2. Use nnUNet for fine segmentation

3. 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 detailed description of the proposed model is shown in Figure. 1.

1 Methods

1.1 Proposed Method

Coarse Segmentation model

The proposed model is implemented made by a dense encoder followed by a non-dense decoder. A dense encoder is chosen to enable the flow of information and gradients throughout the network, facilitating training convergence. The dense encoder consists of 5 dense blocks, each consisting of 6 dense layers followed by a transition layer. Each dense layer consists of 2 convolutional layers with batch normalization (BN) and ReLU activation functions. The first convolutional layer uses a 1 x1 kernel, while the second uses 3 x 3 kernels. The transition layers consist of a BN layer, a 1 x 1 convolutional layer, and a 2 x 2 average pooling layer. The transition layer helps to reduce feature-map size. The dense blocks in the encoder have an increasing number of feature maps at each encoder stage. The model is trained using 5-fold cross-validation. To compute the final prediction, 2D images are stacked to make a 3D segmentation mask. The predicted segmentation mask is further cascaded in a fine segmentation model. The proposed 2D DenseNet model is shown in Figure.1. The Dense block used in the encoder-side of the proposed model is shown in Figure.2.

Fine segmentation model. We have used nnUNet with fivefold cross-validation and selected the best fold for Intracranial Hemorrhage Segmentation, we have modified training and optimization parameters as compared to the original nnUNet. The patch size in nnUNet was 128x128x128 using 500 epochs.

1.2 Training and Optimization details

The proposed deep learning model is implemented in PyTorch and other libraries based on python are used for pre-processing and analysis of the datasets. The SimpleITK is used for reading and writing the nifty data volume. The learning rate of 0.0004 with Adam optimizer has been for training the proposed model. The binary cross-entropy function is used as a loss function between the output of the model and the ground-truth sample. 2 batch-size with 200 epochs has been used with 20 early stopping steps. The best model weights have been saved for prediction in the validation phase. The 256x256x16 input image size was used for training. The Pytorch library is used for model development, training, optimization, and testing. The V100 tesla NVidia-GPU machine is used for training and testing the proposed model. The total training time was 18 hours using a single GPU V100 tesla machine. The data augmentation methods such as HorizontalFlip (p=0.5), VerticalFlip (p=0.5), and RandomGamma (p=0.8) were used to augment the dataset for training the proposed model. The dataset cases have different intensity ranges. The dataset is normalized between 0 and 1 using the max and min intensity normalization method. The training shape of each volume is fixed (256x256x16) and resample the prediction mask to the original shape for each validation volume using the linear interpolation method. The prediction mask produced by our proposed model has been resampled such that it has the same size and spacing as the original image and copies all of the meta-data, i.e., origin, direction, orientation, etc.

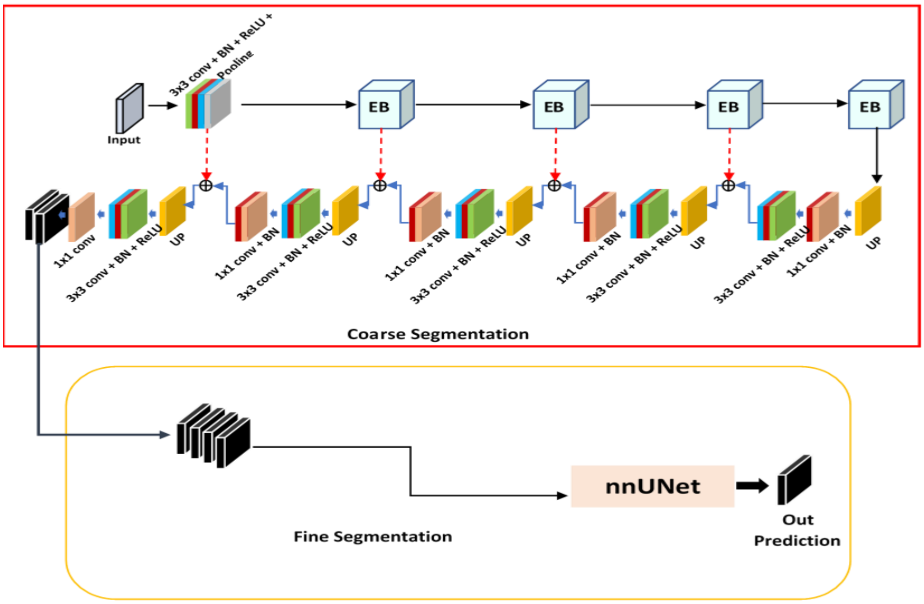

Figure.1. Proposed solution for Intracranial Hemorrhage Segmentation Challenge on Non-Contrast head CT (NCCT).

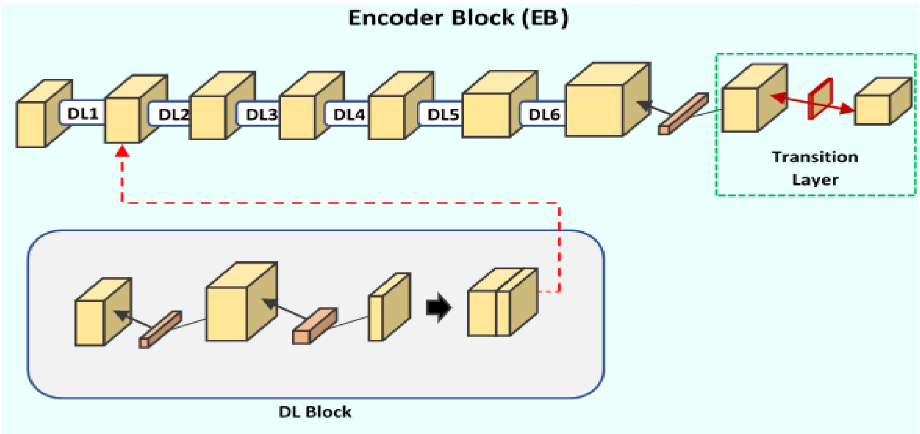

Figure. 2. The encoder module is based on proposed DensNet blocks (DL: Dense Layer).

2 Dataset

The challenge organizers collected 200 non-contrast head CT volumes of clinically diagnosed patients with different kinds of ICH, including subdural hemorrhage, epidural hemorrhage, intraventricular hemorrhage, intraparenchymal hemorrhage, and subarachnoid hemorrhage. Those CT volumes are obtained from the Peking University Shougang Hospital, China. The data were well labeled by 10 radiologists with more than 5 years of clinical experience. The size of a CT volume is 512*512*N, where N lies in [20,70]. The pixel spacing of a CT volume is 0.42mm*0.42mm*5mm. The images will be stored in NIFTI files. Voxel-level segmentation annotations are: 0 - Background; 1 – ICH. A detailed description is found [2-3]

3 Conclusion

In this paper, we have developed a coarse and fine segmentation model for intracranial hemorrhage segmentations. We have trained two different models for intracranial hemorrhage segmentations. Proposed 2DDensNet is used in coarse segmentation and nnUNet has been applied in fine segmentation. In the future, we will explore other 3D single segmentation methods to further enhance the performance of the ICH segmentation.

Acknowledgment

The authors of this paper declare that the segmentation method they implemented for participation in the Instance2022 challenge has not used any pre-trained models or additional datasets other than those provided by the organizers. We thank the Instance2022 challenge organizer teams who provided the dataset and platform to validate our proposed solution.

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