Automated ischemic stroke lesion segmentation from 3D MRI
ISLES 2022 challenge report

Md Mahfuzur Rahman Siddiquee, Dong Yang, Yufan He, Daguang Xu, and
Andriy Myronenko
NVIDIA, Santa Clara, CA
{mdmahr,dongy,yufanh,daguangx,amyronenko}@nvidia.com

Abstract. Ischemic Stroke Lesion Segmentation challenge (ISLES 2022) offers a platform for researchers to compare their solutions to 3D segmentation of ischemic stroke regions from 3D MRIs. In this work, we describe our solution to ISLES 2022 segmentation task. We re-sample all images to a common resolution, use two input MRI modalities (DWI and ADC) and train SegResNet semantic segmentation network from MONAI. The final submission is an ensemble of 15 models (from 3 runs of 5-fold cross-validation). Our solution (team name NVAUTO) achieves the top place in terms of Dice metric (0.824), and overall rank 2 (based on the combined metric ranking\footnote{\url{https://isles22.grand-challenge.org/}}). It is implemented with Auto3Dseg\footnote{\url{https://monai.io/apps/auto3dseg}}.

Keywords: ISLES22 · MICCAI22 · segmentation challenge · MONAI · Auto3Dseg · SegResNet · 3D MRI.

1 Introduction

Segmentation of ischemic stroke region is necessary for treatment planning and evaluation of patients’ disease outcomes. Ischemic Stroke Lesion Segmentation challenge (ISLES 2022) aims to benchmark infarct segmentation in acute and sub-acute stroke using multimodal 3D MRI modalities\footnote{\url{https://isles22.grand-challenge.org/}}. The ISLES22 dataset consists of 400 cases (250 labeled labeled cases were provided for training, and 150 reserved for testing). Each case includes three 3D MRI modalities (DWI, ADC and FLAIR), and the task is to segment a single class (stroke region). The images were skull stripped and intensity normalized by the organizers. The ground truth labels were provided in the reference space of DWI and ADC image modalities. The FLAIR image modality is at a higher resolution, and also slightly misaligned from the reference frame (in this work we decided not use the FLAIR modality, and use only DWI and ADC images). An example case with 3D MRIs and the corresponding ground-truth overlays is shown in Figure\footnote{\url{https://isles22.grand-challenge.org/}}.
Fig. 1. An example of 3D MRIs (DWI, ADC and FLAIR) images showing ischemic stroke region (in red).

Fig. 2. SegResNet network configuration. The network uses repeated ResNet blocks with Instance normalization, and deep supervision in the decoder branch.

2 Method

We implemented our approach with MONAI\(^3\), we used Auto3Dseg\(^4\) system to automate most parameter choices. For the main network architecture we used SegResNet\(^5\), which is an encode-decoder based semantic segmentation network based on [7], with deep supervision (see Figure 2).

The encoder part uses ResNet \(^5\) blocks with instance normalization. We have used 5 stages of down-sampling, each stage has 2, 4, 4, 4, and 4 convolutional blocks, respectively. Each block’s output is followed by an additive identity skip connection. We follow a common CNN approach to downsize image dimensions by 2 progressively and simultaneously increase feature size by 2. All convolutions are 3x3x3 with an initial number of filters equal to 32. The encoder is trained with 192 x 192 x 128 input region. The decoder structure is similar to the encoder one, but with a single block per each spatial level. The end of the decoder has

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\(^3\) https://github.com/Project-MONAI/MONAI
\(^4\) https://monai.io/apps/auto3dseg
\(^5\) https://docs.monai.io/en/stable/networks.html#segresnet
the same spatial size as the original image, and the number of features equal to
the initial input feature size, followed by a 1x1x1 convolution and a softmax. For
the deep supervision of 3 sub-levels of the decoder branch features, we add extra
projections heads (1x1x1 convolutions) into the same number of output classes.
These additional network outputs are used to compute losses at smaller image
scales.

Dataset  We use the ISLES dataset \cite{6} for training the model. We randomly
split the entire dataset into 5 folds and trained a model for each fold.

Data preparation  We use only DWI and ADC image modalities, re-sample
them to a common 1x1x1mm resolution, and concatenate into a two channel 3D
input.

Data normalization  We normalize each MRI image to a zero mean and unit
std.

Cropping  We crop a random patch of 192x192x128 voxels, which includes most
of the foreground content. We use the batch size of 1.

Augmentations  We use random a) flips (all axes) b) random rotation and
scaling, c) random smoothing, noise, intensity scale/shift.

Loss  We use the combined Dice + Focal loss. The same loss is summed over all
deep-supervision sublevels:

\[
Loss = \sum_{i=0}^{4} \frac{1}{2^i} Loss(pred, target^i)
\]

where the weight \( \frac{1}{2^i} \) is smaller for each sublevel (smaller image size) \( i \). The target
labels are downsized (if necessary) to match the corresponding output size using
nearest neighbor interpolation.

Optimization  We use the AdamW optimizer with an initial learning rate of
\( 2e^{-4} \) and decrease it to zero at the end of the final epoch using the Cosine
annealing scheduler. All the models were trained for 1000 epochs with deep
supervision. We use batch size of 1 per GPU, and train on 8 GPUs 16Gb NVIDIA
V100 DGX machine (which is equivalent to batch size of 8). We use weight decay
regularization of \( 1e^{-5} \).

Pretraining  We pretrain the network on Brats21 dataset using the same net-
work configuration \cite{3}. In our experiments, the pretraining slightly increases the
cross-validation dice accuracy (0.5-1%).
3 Results

Based on our data splits, a single run 5-folds cross-validation results are shown in Table 1. On average, we achieve 0.8086 cross-validation performance in terms of dice metric (see Table 1).

![Table 1. Average DICE among classes using 5-fold cross-validation.](image)

For the final submission we use a mean ensemble of 15 models total (3 fully trained runs, using best checkpoints). Table 2 shows the final ranking and scores on the hidden test sets (provided by the organizers) for the top 3 places. Our solution (NVAUTO) team achieves the best dice accuracy, but ranks 2nd overall based on all 4 metrics used in this challenge (Dice, F1-score, Average volume difference, lesion count difference).

![Table 2. Top 3 teams of the ISLES22 challenge with the corresponding 4 metrics used for the final ranking.](image)

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