Progressive Deep Learning: An Accelerated Training Strategy for Medical Image Segmentation

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INTRODUCTION

- Continuous advancement in the application of deep learning (DL)-based approaches to medical tasks has seen DL achieve state-of-the-art performance in a wide range of applications including object recognition, classification, and medical image segmentation.
- Training DL models, however, is a computationally and time intensive process due to the complex nature of modern network architectures and the size of training datasets.
- Moreover, hyperparameter selection is a manual and repetitive process intended to optimize network performance.
- In this study, we present a novel training acceleration strategy in which training datasets are progressively fed to the network based on similarity measurements for medical image segmentation – an approach we term Progressive DL (PDL).

METHOD

- **CT: Experiment**
  - 30 Breast CT dataset were acquired.
  - 24 datasets for training, 6 sets for validation.
  - Clinical contours of the left breast, right breast, and heart were used.
- **MRI: Experiment**
  - 24 Breast MRI dataset were acquired.
  - 20 datasets for training, 4 sets for validation
  - Clinical contours of the left breast, right breast, and heart were used.
- **Preprocessing**
  - PDL was evaluated in the thoracic auto segmentation task for both CT and MR images.
  - Training datasets were ranked in similarity using the mean square error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM) metrics.
  - Image registration was done for accurate similarity calculation.
- **PDL model training**
  - The entirety of the training dataset into two divided sets: Set 1, the most dissimilar data; and Set 2, the remaining data.
  - In the first step of PDL, the model is trained using only the most dissimilar data until a fixed number of epochs have been completed.
  - Add the remaining data in Set 2, training commences again before terminating at a fixed Dice similarity coefficient (DSC) computed for the validation set.

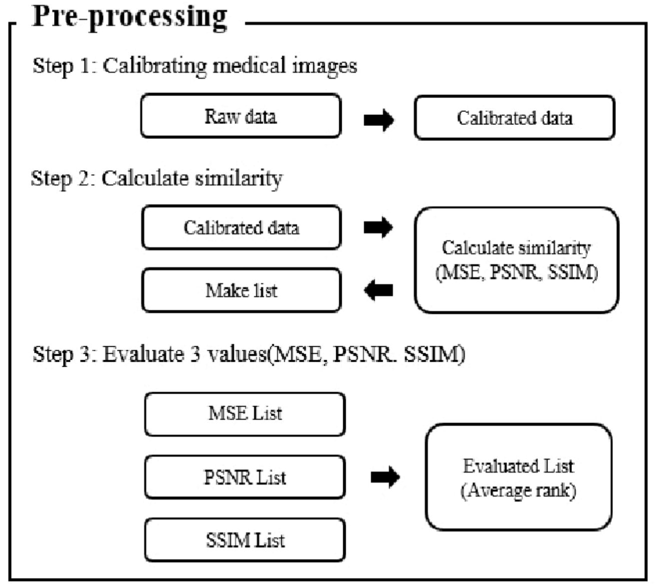

Figure 1. Pre-processing framework

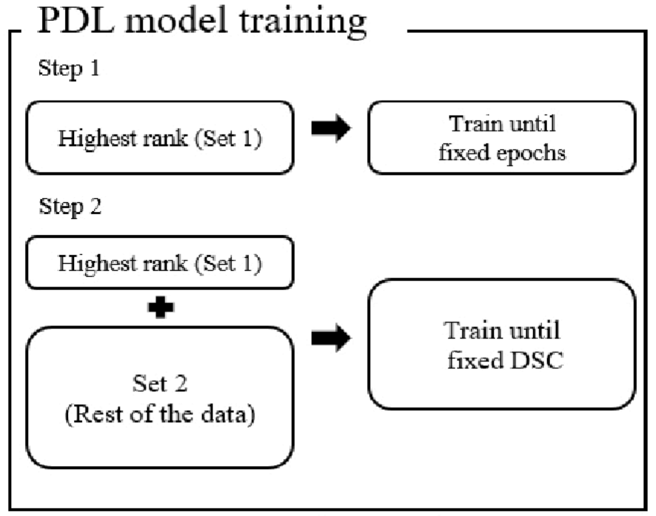

Figure 2. PDL model training framework

RESULTS

- DSC scores computed over the validation set are presented in Figs. 3 and 4 for the CT and MRI segmentation tasks, respectively.
- CT
  - The PDL model required 43% less time to reach the fixed DSC score at which training was terminated compared to the conventional DL model, down to 20386 seconds from 35777 seconds.
- MRI
  - The PDL model required 56% less time to reach the termination condition, reducing training time to 4457 seconds compared to 10160 seconds for the conventional training strategy.
- In table 1 & 2 we can see that as accuracy increases the more time is needed for CDL to reach the accuracy compared to PDL.
- Although the focus of the present study was the medical image segmentation task, we expect the same benefit may be achieved when PDL is adopted in other tasks.

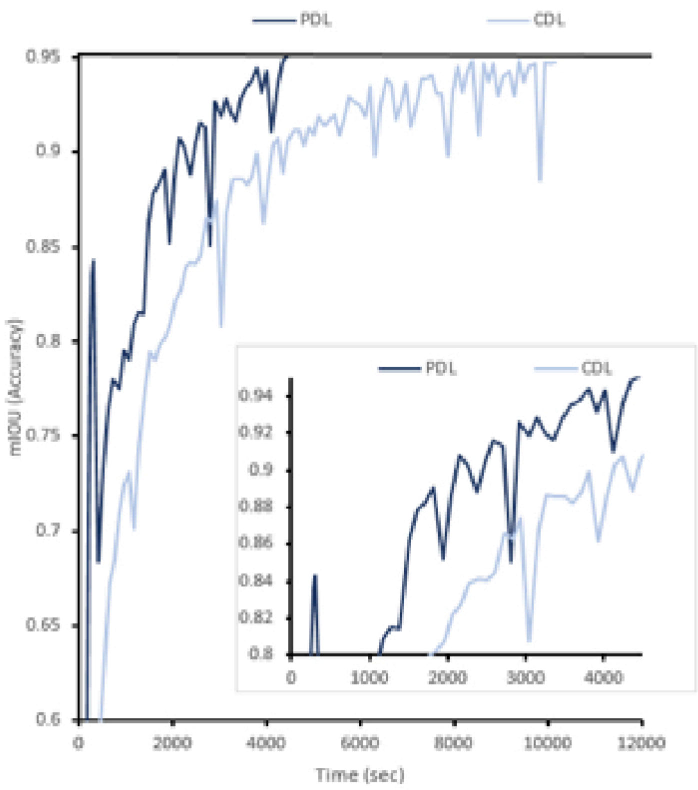

Figure 3. PDL and CDL model results in CT

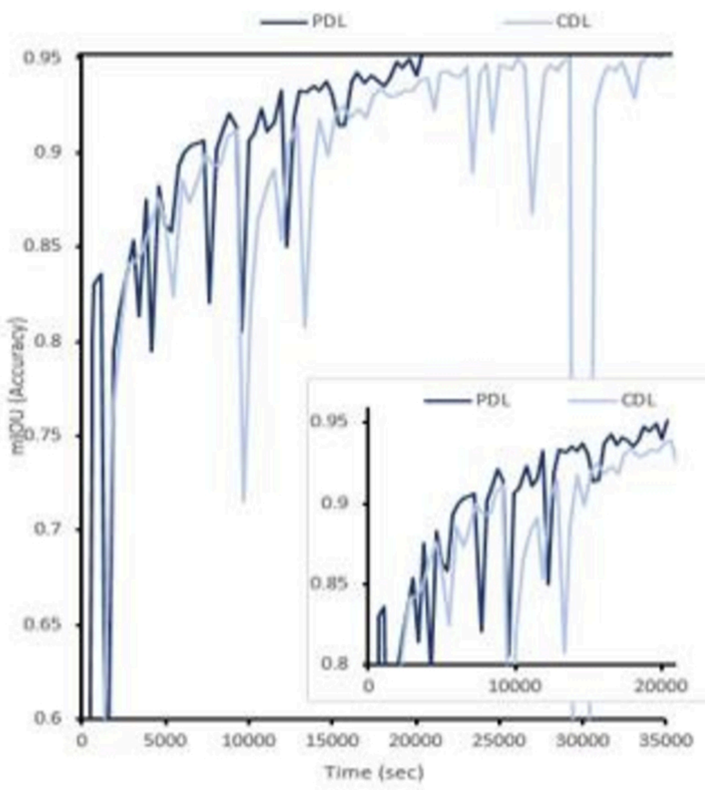

Figure 4. PDL and CDL model results in MRI

PDL		CDL		Ratio
Time	Accuracy	Time	Accuracy	
1892.8	0.7944	2298.8	0.8072	0.8234
3048.26	0.8531	4137.83	0.8641	0.7367
6508.27	0.9038	8737.38	0.9075	0.7449
20385.63	0.9516	35777.06	0.9562	0.5698

Table 1. Ratio of time to reach the accuracy in CT

PDL		CDL		Ratio
Time	Accuracy	Time	Accuracy	
1174.69	0.8095	1844.74	0.802	0.6368
1497.84	0.8623	2721.43	0.866	0.5504
2152.02	0.9076	4140.34	0.9034	0.5198
4457.01	0.9508	10160.1	0.9477	0.4387

Table 2. Ratio of time to reach the accuracy in MRI

CONCLUSIONS

- The proposed PDL accelerated training strategy for medical image segmentation offers the potential to reduce training time while maintaining task-critical performance.
- We expect the PDL strategy to be applicable to tasks beyond segmentation given the establishment of similarity metrics relevant to the task.

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