Lifelong Learning with Dynamic Convolutions for Glioma Segmentation from Multi-Modal MRI

Subhashis Banerjee and Robin Strand
Department of Information Technology, Uppsala University, Sweden

INTRODUCTION

➔ Gliomas are the most common type of primary brain tumor accounting for 40% of all CNS tumors and 80% of malignant brain tumors [1].

➔ Manual segmentation of Gliomas from MRI is time-consuming and subjected to high inter-and intra-observer variation [2].

➔ Convolutional Neural Networks (CNNs) have been shown to perform impressively on brain tumor segmentation but require a large amount of training data [2, 3, 4].

➔ Which is a time-consuming and costly task involving the precious time and effort of radiologists. Other difficulties lie in obtaining diverse annotated training data that covers the entire spectrum of potential situations along with consistent MRI modalities for each training sample.

➔ Recently Lifelong Learning (LL) [5] proposed a feasible solution using sequential knowledge acquisition through continual learning from the new set of training data, along with enhancing the existing knowledge gained from the previous training.
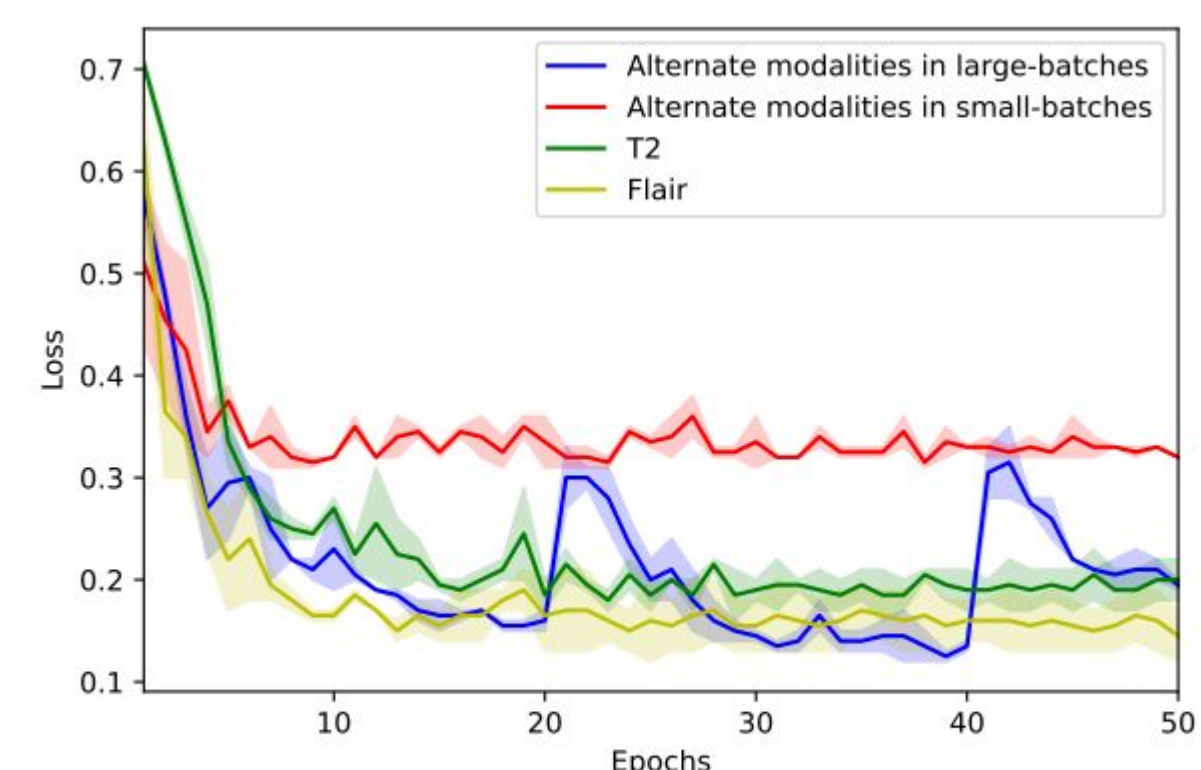
Figure 1. LL training performance of static CNN model for Glioma segmentation in three different settings.

➔ Although it appears like an easy-to-implement solution, significant difficulty involves due to catastrophic forgetting, which occurs when a network's parameters are changed during adaptation to the new set of training data.

➔ In this paper, we consider one of the possible practical scenarios, i.e., non-uniform MRI modalities in training samples.

➔ Fig. 1 illustrates the LL training performance of a U-Net [6] based segmentation network for Glioma segmentation in three different settings. Lifelong training with small or large batches of alternate modalities leads to "catastrophic forgetting".

In this paper, we propose a solution using dynamic convolution to encounter catastrophic forgetting. We proposed a Dynamic Convolution Neural Network (Dy-CNN) [7] based segmentation network for Glioma segmentation, and show its suitability in a lifelong sequential learning-based scenario with multi-modal MR images.

METHODS

The purpose of dynamic convolution is to learn a set of kernel coefficients or weights to convert the fixed kernels into a dynamic one. Fig. 2(a) depicts the general architecture of dynamic convolution [7, 8]. It predicts the kernel coefficients using a trainable attention coefficient prediction module. Then, the fixed convolution kernels are multiplied by the dynamic weights to form a set of dynamic convolution kernels based on the training batch.
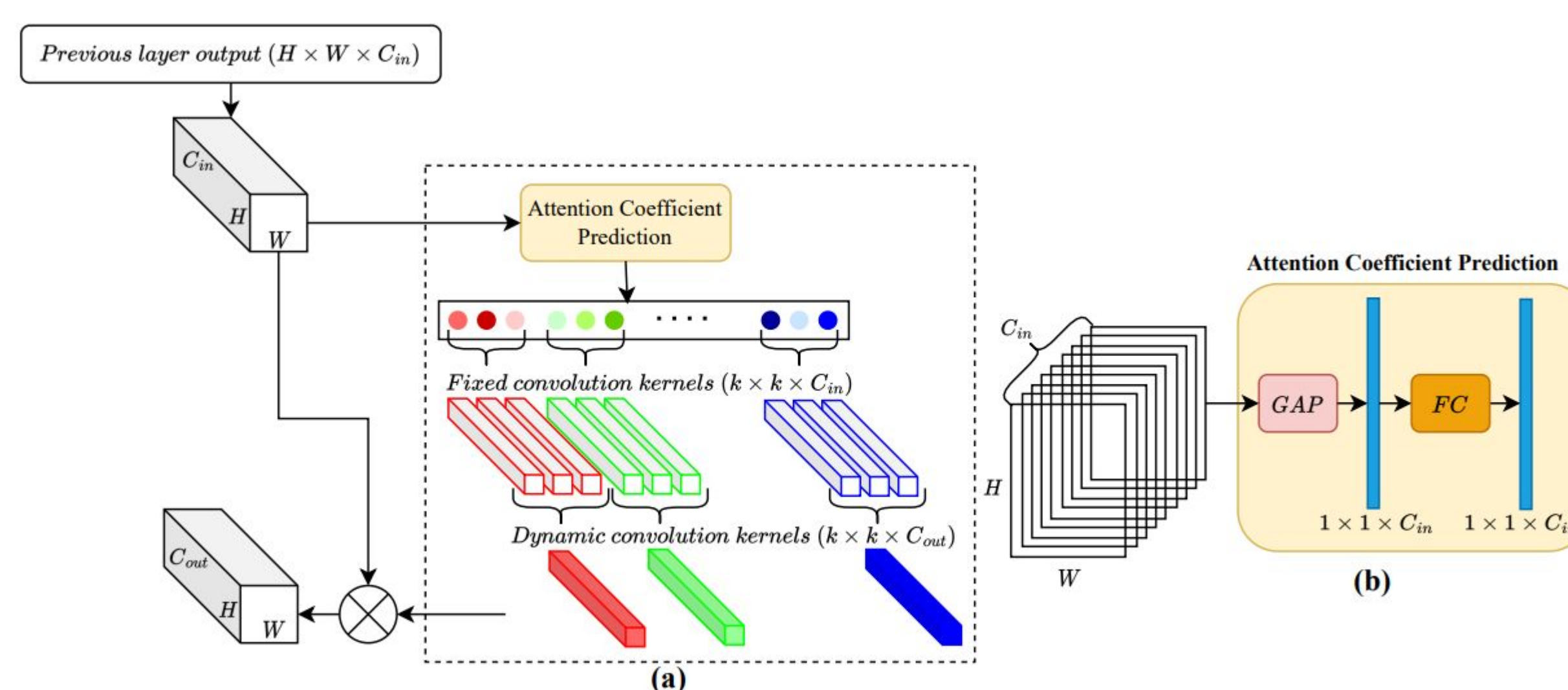
Figure 2. (a) Dynamic Convolution and (b) Attention coefficient prediction module.

The purpose of the ACP module is to predict coefficients or weight values for each fixed convolution kernel in the convolution layer to convert them into dynamic convolution kernels based on the input as shown in Fig. 2(b).

To produce dynamic Convolution Kernels of size $k \times k \times C_{Out}$, the dynamic convolution kernel generation layer uses $k \times k \times C_{in}$ fixed convolution kernels (based on the number of response maps generated from the previous layer) and corresponding attention weight vector of size $1 \times 1 \times C_{in}$ generated by the ACP module as follows.

$$\tilde{w}_1, \tilde{w}_2, \cdots, \tilde{w}_{C_{out}} = \sum_{i=1}^{g_t} \alpha_i \cdot w_i, \sum_{i=g_t}^{g_t \times 2} \alpha_i \cdot w_i, \cdots, \sum_{i=C_{in}-g_t}^{C_{in}} \alpha_i \cdot w_i$$
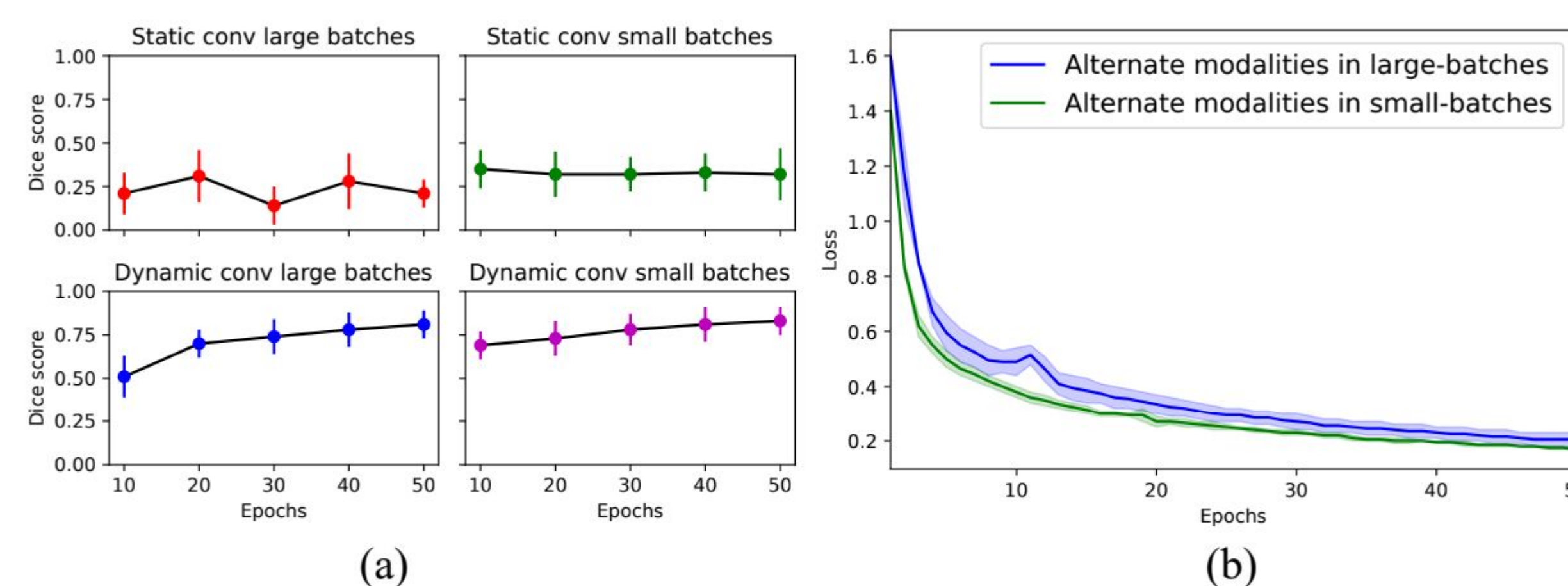
Figure 3. (a) Segmentation performance of CNN with static convolution vs Dy-CNN with large and small batches in a LL based training scheme. (b) Learning curves of Dy-CNN based segmentation network.

RESULTS

➔ We have collected T2 and Flair MRI volumes from 130 Glioma patients (pre-operative multi-institutional scans) from The Cancer Imaging Archive (TCIA) Glioblastoma Multiforme (TCGA-GBM) data collection [2, 3].

➔ For model training, we randomly selected 110 patients and used 55 patients with only T2 volume and the remaining 55 with Flair volume. The remaining 20 patients are used as the test set, among which 10 patients are used with T2 volume, and the remaining 10 are used with Flair volume for testing the models' performance.

➔ LL-based training approach is used to train the models. Streams of training data are coming in small or large batches consisting of alternate MRI modalities as being curated from hospitals.

➔ As shown in Fig. 3(b) Dy-CNN-based segmentation network is robust to catastrophic forgetting. Whereas in static CNN base segmentation networks, LL-based training can not be pursued due to the catastrophic forgetting preventing the training process to be converged and modeled to learn as illustrated in Fig. 1.

CONCLUSIONS

Here we have presented a novel Dy-CNN-based segmentation network for Glioma segmentation and experimentally demonstrated its suitability in a lifelong sequential learning-based scenario with multi-modal MR images. Experimental results demonstrated the superiority of the Dy-CNN-based segmenting network in terms of learning through multi-modal MRI images and better convergence of lifelong learning-based training.

REFERENCES

1. Wirsching, H.-G. and Weller, M., "Glioblastoma," Malignant Brain Tumors , 265–288 (2017).

2. Kamnitsas, K., Ferrante, E., Parisot, S., et al., "Deepmedic for brain tumor segmentation," in [International workshop on Brainlesion: Glioma, multiple sclerosis, stroke and traumatic brain injuries], 138–149, Springer (2016).

3. Banerjee, S. and Mitra, S., "Novel volumetric sub-region segmentation in brain tumors," Frontiers in Computational Neuroscience 14, 3 (2020).

4. Banerjee, S., Toumpanakis, D., et al., "Topology-aware learning for volumetric cerebrovascular segmentation," in [2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI)], 1–4, IEEE (2022).

5. Sodhani, S., Faramarzi, M., et al., "An introduction to lifelong supervised learning," arXiv preprint arXiv:2207.04354 (2022).

6. Ronneberger, O., Fischer, P., and Brox, T., "U-net: Convolutional networks for biomedical image segmentation," in [International Conference on Medical image computing and computer-assisted intervention], 234–241, Springer (2015).

7. Chen, Y., Dai, X., Liu, M., et al., "Dynamic convolution: Attention over convolution kernels," in [Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition], 11030–11039 (2020).

8. Zhang, Y., Zhang, J., Wang, Q., and Zhong, Z., "Dynet: Dynamic convolution for accelerating convolutional neural networks," arXiv preprint arXiv:2004.10694 (2020).