Semantic Segmentation of 3D Medical Images Through a Kaleidoscope: Data from the Osteoarthritis Initiative

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Boyeong Woo[1], Marlon Bran Lorenzana[1], Craig Engstrom[2], William Baresic[2], Jurgen Fripp[1,3], Stuart Crozier[1], Shekhar S. Chandra[1]

[1] School of Information Technology and Electrical Engineering, University of Queensland, Australia
[2] School of Human Movement and Nutrition Sciences, University of Queensland, Australia
[3] Australian eHealth Research Centre, Commonwealth Scientific and Industrial Research Organisation, Australia

Introduction

While there have been many studies on using deep learning for medical image analysis, the lack of manually annotated data remains a challenge in training a deep learning model for segmentation of medical images. This work shows how the kaleidoscope transform (KT), proposed by [1], can be applied to a 3D convolutional neural network to improve its generalizability when the training set is extremely small.

Materials and Methods

This study used 38 knee MR images (consisting of examinations of 25 patients) from the publicly available Osteoarthritis Initiative (OAI) database [2].

In this study, the kaleidoscope transform, $(\nu, 1)$-KT, with a downsampling factor ν was efficiently achieved via element reordering as in [3] (Fig. 1).

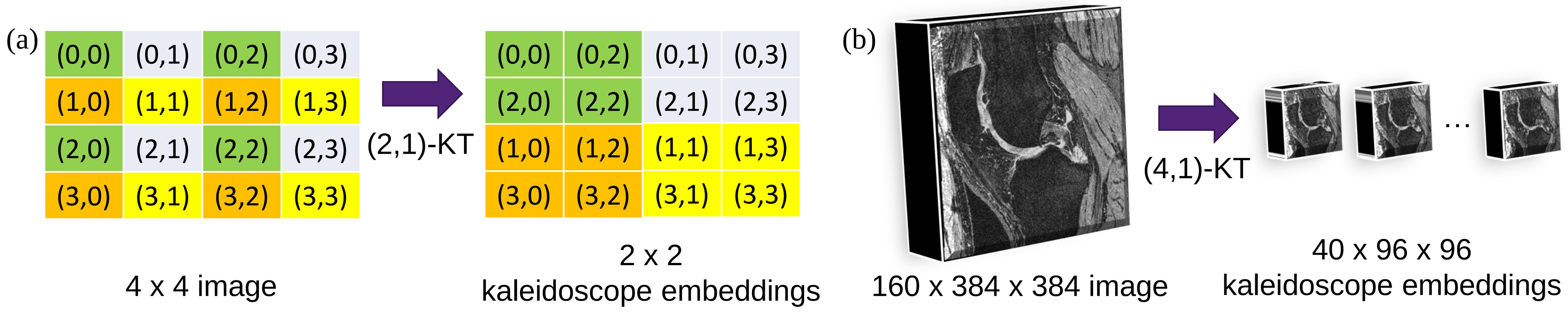

Figure 1. (a) (2,1)-KT for a small 2D image. (b) (4,1)-KT for a 3D image. A 3D input image is decomposed into an array of 64 downsampled images.

The KT was applied to a context aggregation network (CAN) [4] for semantic segmentation of anatomical structures in knee MR images. The proposed model, KAN3D, is shown in Fig. 2.

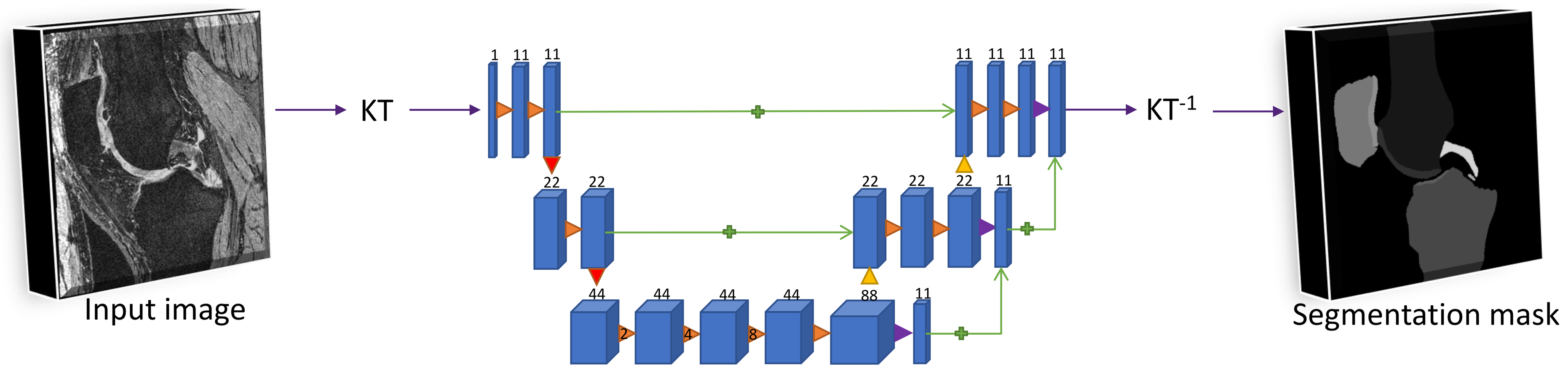

Figure 2. The KAN3D. The input image is rearranged into a batch of downsampled images (KT) before the convolution operations, and then the voxels are rearranged back to their original positions (KT^{-1}) after the convolution operations to produce the predicted segmentation mask for the input image.

Results

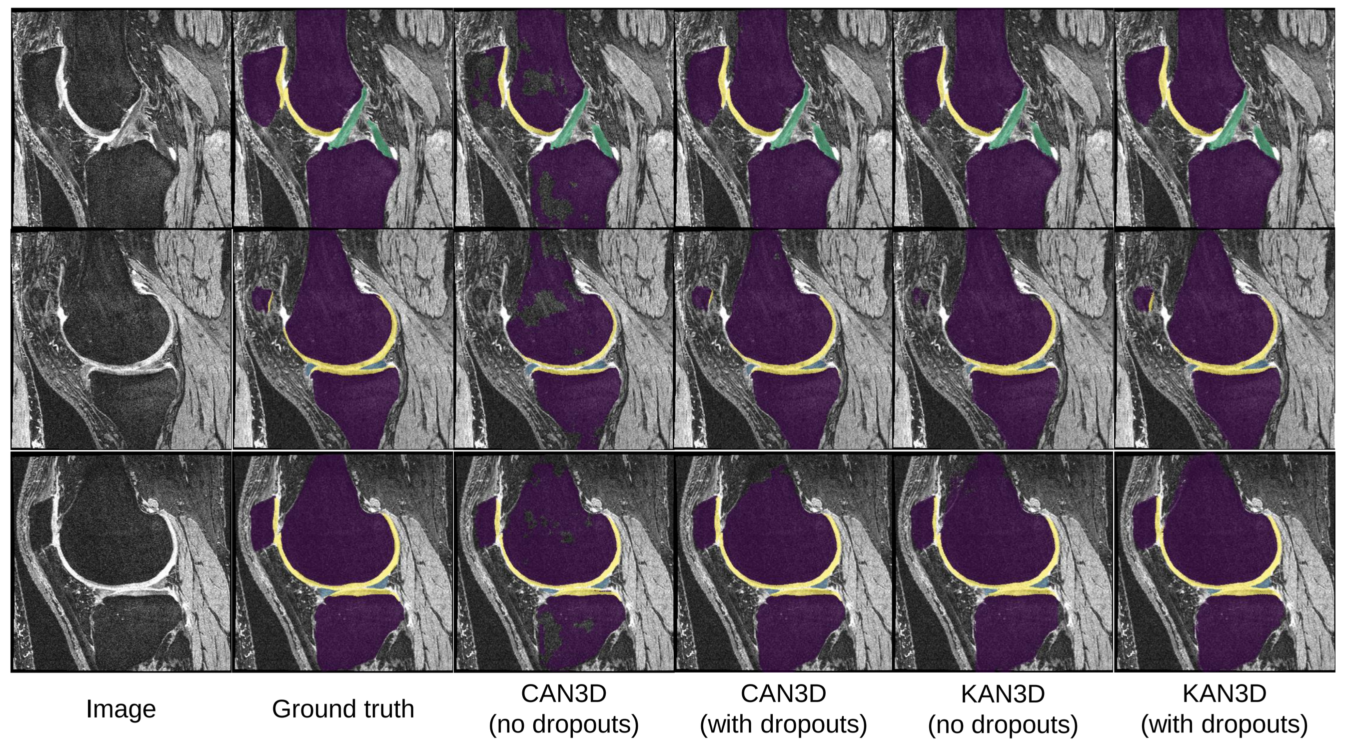

Figure 3. Example outputs from KAN3D and CAN3D (without the KT) trained with or without dropouts.

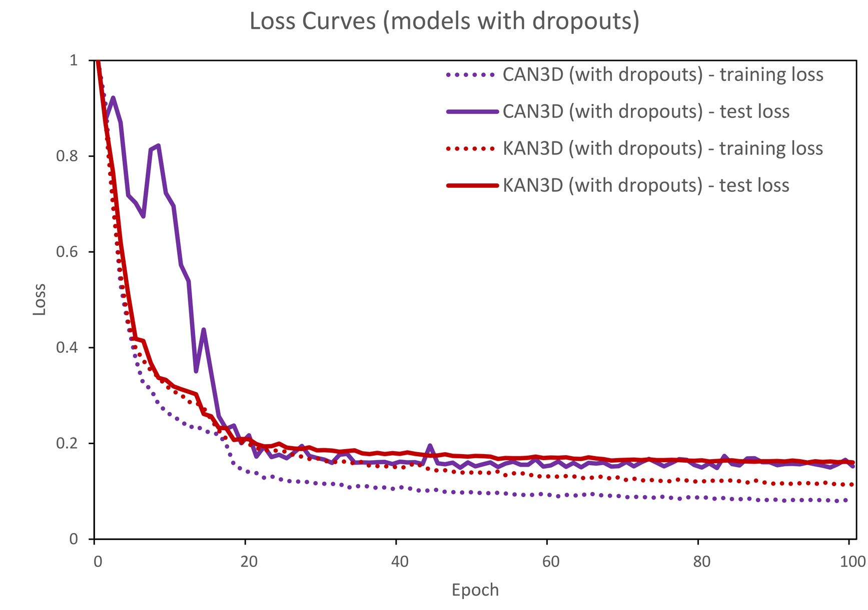

Figure 4. Loss curves showing training loss and test loss over epochs for KAN3D and CAN3D trained with dropouts.

Discussion and Conclusion

The KAN3D model has benefits of both patch-based and volume-based approach.

- KAN3D with dropouts generalizes well without the need for data augmentation when the training set is extremely small (an advantage of patch-based approach).
- Yet, since the patches are put back together at the end, it preserves the overall 3D structure and only requires a single inference, having a fast inference time (an advantage of volume-based approach).

However, the current study also demonstrated the model's limitations, including limited accuracy in the segmentation of small structures. Future studies are expected to include adding further improvements to the model.

References

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b.woo@uqconnect.edu.au