SIIM CAIMI25
Conference on Artificial Intelligence in Medical Imaging
OCT 20-21 | UNIVERSITY OF CALIFORNIA, IRVINE

GUSL: A Novel and Efficient Machine Learning Model for Kidney Segmentation

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Introduction/Background

More than 430,000 individuals are diagnosed with kidney cancer annually, leading to approximately 180,000 deaths each year. The precise segmentation of the kidney is clinically significant and aids clinicians in preoperative surgical planning. Manual segmentation is a time-consuming and labor-intensive task for radiologists. AI can provide fast, reliable, and accurate automatic segmentation. We propose a new feed-forward and lightweight machine learning framework without backpropagation, named Green U-shaped Learning (GUSL).

Methods/Intervention

GUSL is a novel machine learning model for 3D medical image segmentation without backpropagation or neural networks, but instead learns visual representations in a feed-forward manner. A two-stage approach is developed to tackle the class imbalance issue and emphasize training on the challenging areas of the prostate, particularly its boundaries. An essential aspect of the GUSL model is the residue correction at each level in a bottom-up manner, aiming to predict the residual map rather than just a segmentation mask. In this way, we could introduce an attention mechanism to focus on the boundary part and remove other irrelevant foreground and background. The prediction of the residual map is obtained and then added to the previous prediction mask to boost the performance level by level.

Results/Outcome

We applied the GUSL on the KiTS23 challenge dataset, which contains 489 patients. I randomly divide the data into a training set (391 patients) and a testing set (98 patients). I also applied three deep learning methods on it for benchmarking. As shown in the table, GUSL achieves the highest Dice Similarity Coefficient (DSC) of 0.968, slightly outperforming nnU-Net (0.967), while significantly reducing the number of parameters (1.13M vs. 31.2M) and computational cost (7.11B vs. 346B FLOPs). Compared to U-Net and V-Net, which achieve DSCs of 0.886 and 0.856, respectively, GUSL shows superior accuracy with 16–40× fewer parameters and 2–53× fewer FLOPs.

Conclusion

As shown in the table, the GUSL could achieve the highest Dice Similarity Coefficient (DSC), and in the meantime keep the lowest model size and FLOPs.

Statement of Impact

Not only did we achieve the highest performance on the KiTS23 dataset, but we also significantly reduced the model's size and complexity compared to other models.

Method	DSC for Kidney and Masses	# of parameters	FLOPs
U-Net	0.886	17,970,626 (×16)	13.6B (×2)
V-Net	0.856	45,603,934 (×40)	379B (×53)
nnU-Net	0.967	31,195,594 (×28)	346B (×49)
GUSL	**0.968**	**1,132,176 (×1)**	**7.11B (×1)**

We compare the performance and efficiency of several segmentation methods on kidney and tumor structures.

Keywords
Machine learning; Medical imaging; Feed-forward model; Kidney segmentation