THE IMPACT OF STATE SPACE AND DIMENSIONALITY ON PANCREATIC ULTRASOUND TUMOR SEGMENTATION

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Accurate segmentation of pancreatic tumors is crucial for PDAC diagnosis and monitoring drug response, which remains challenging. We employed 2D and 3D U-MAMBA and Residual U-Net for tumor segmentation on ultrasound images. 3D U-MAMBA performed best, achieving a 72% Dice score.

1. INTRODUCTION

Pancreatic ductal adenocarcinoma (PDAC) is the third leading cause of cancer-related deaths in the United States, with a median survival of less than 6 months [1] post-diagnosis. Late detection is a contributing factor to poor prognosis, necessitating non-invasive tools for early detection and monitoring. While ultrasound is a non-invasive technique for imaging pancreatic tumors [2], it suffers from noise susceptibility, minimizing tumor boundary detection. Additionally, manual segmentation is time-consuming, introduces rater variability, and thus impacts tumor growth tracking accuracy.

To address these challenges, we evaluate the performance of U-MAMBA (UM) and Residual U-Net (R-UN) in both 2D and 3D configurations to assess the influence of state space components and dimensionality for producing optimal baseline tumor segmentations.

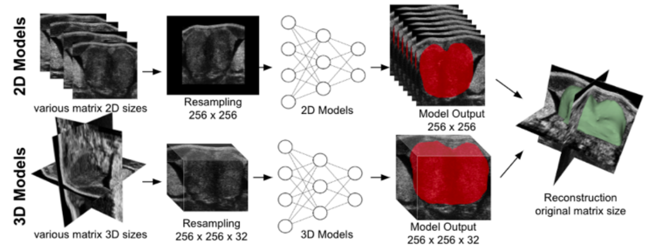
2. METHODS

B-mode ultrasound scans were acquired from 178 mice (107 KPC [1] and 71 Orthotopic) using a FujiSonics Series 3100 ultrasound scanner (Columbia University). Tumors were semi-manually segmented in VevoQ by an expert, manually delineating every other slice with subsequent lesion filling.

We implemented U-MAMBA [3] and Res U-Net [4] in both 2D and 3D configurations for our tumor segmentation task. All networks employed a patch-based approach (whole image shape: 256x256x32) and were trained using the AdamW optimizer with a Dice Cross-Entropy loss function. The network consisted of double convolutions with batch normalization. All models were trained with a batch size of 16, a learning rate of 1e-4, and a 60/20/20 split for training/validation/testing for 50 epochs.

Model performances were evaluated using dice, F1, sensitivity, specificity, and accuracy metrics.

3. RESULTS AND CONCLUSION



Model	Dice	F1	Sensitivity	Specificity	Accuracy
2D UM	0.63	0.68	0.74	0.95	0.95
2D R-UN	0.67	0.72	0.84	0.95	0.94
3D UM	0.72	0.77	0.85	0.96	0.95
3D R-UN	0.67	0.71	0.80	0.95	0.94

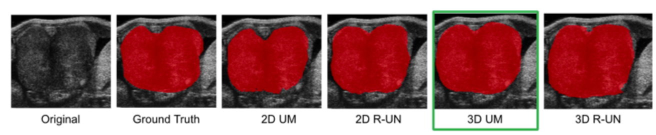


Fig. 1. Pipeline, fit metrics, and sample segmentation across models.

The 3D UMAMBA model achieved the best performance, with the potential for further improvement through hyperparameter tuning. These results highlight the potential of state space models with higher dimensions for lesion segmentation and reliable quantitative imaging.

4. REFERENCES

[1] S. Hu *et al.*, "Non-invasive dynamic monitoring initiation and growth of pancreatic tumor in the LSL-KrasG12D/+;LSL-Trp53R172H/+;Pdx-1-Cre (KPC) transgenic mouse model," *J. Immunol. Methods*, vol. 465, pp. 1–6, Feb. 2019.

[2] A. Sofuni, T. Tsuchiya, and T. Itoi, "Ultrasound diagnosis of pancreatic solid tumors," *J. Med. Ultrason.*, vol. 47, no. 3, pp. 359–376, Jul. 2020.

[3] J. Ma, F. Li, and B. Wang, "U-Mamba: Enhancing Long-range Dependency for Biomedical Image Segmentation," 2024, *arXiv*.

[4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA: IEEE, Jun. 2016, pp. 770–778.