



UNIVERSITY OF CENTRAL FLORIDA

# CAP 5516 Assignment 3: Parameter Efficient Fine- tuning Foundation Model for Nuclei Instance Segmentation

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*This report presents details of the implementation of the Assignment 3 where MobileSAM and LoRa were used for Nuclei Instance Segmentation task.*

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Submitted By:

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## 1 Introduction

This project focuses on applying parameter-efficient fine-tuning to the Segment Anything Model (SAM) for nuclei instance segmentation in H&E-stained histological images using the NuInsSeg dataset. For computational efficiency, MobileSAM, which is a lightweight variant of SAM and fine-tune it is using LoRA (Low-Rank Adaptation) has been utilized. The goal is to outperform baseline segmentation models using fewer tunable parameters while maintaining or improving segmentation quality.

## 2 Dataset and Preprocessing

dataset used is NuInsSeg: A Fully Annotated Dataset for Nuclei Instance Segmentation [1], consisting of H&E-stained histological images with pixel-level instance annotations across 31 human and mouse organs.

Dataset sources:

Kaggle link: <https://www.kaggle.com/datasets/ipateam/nuinsseg/>

GitHub repo: <https://github.com/masih4/NuInsSeg>

Zenodo archive: <https://zenodo.org/records/10518968>

Figure 01 shows the tissue images of the human kidney (left) and mouse kidney (right). On the other hand, Figure 02 shows the tissue image and its corresponding segmentation mask. Figure 03 also shows the image and mask pair sample.

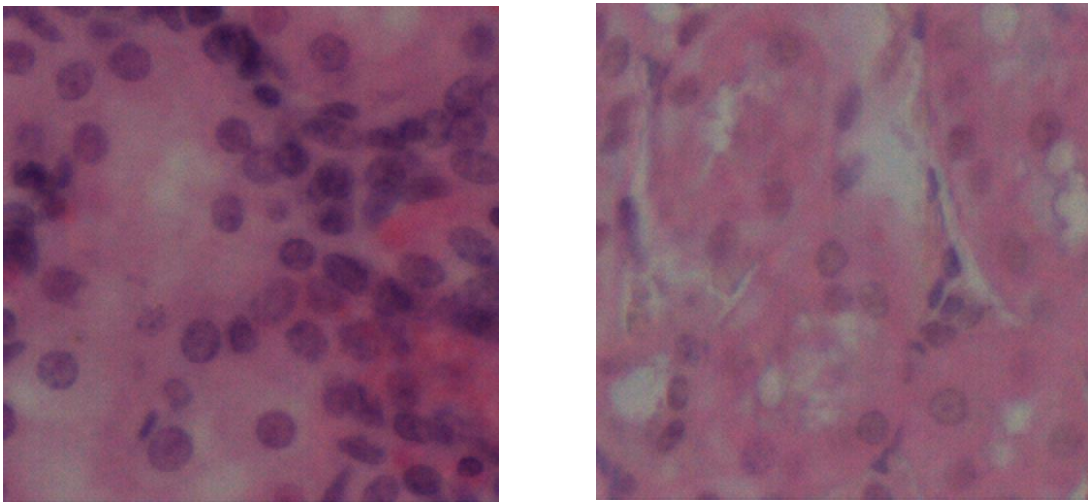


Figure 01: Dataset Sample of the Tissue images of Human Kidney and Mouse Kidney

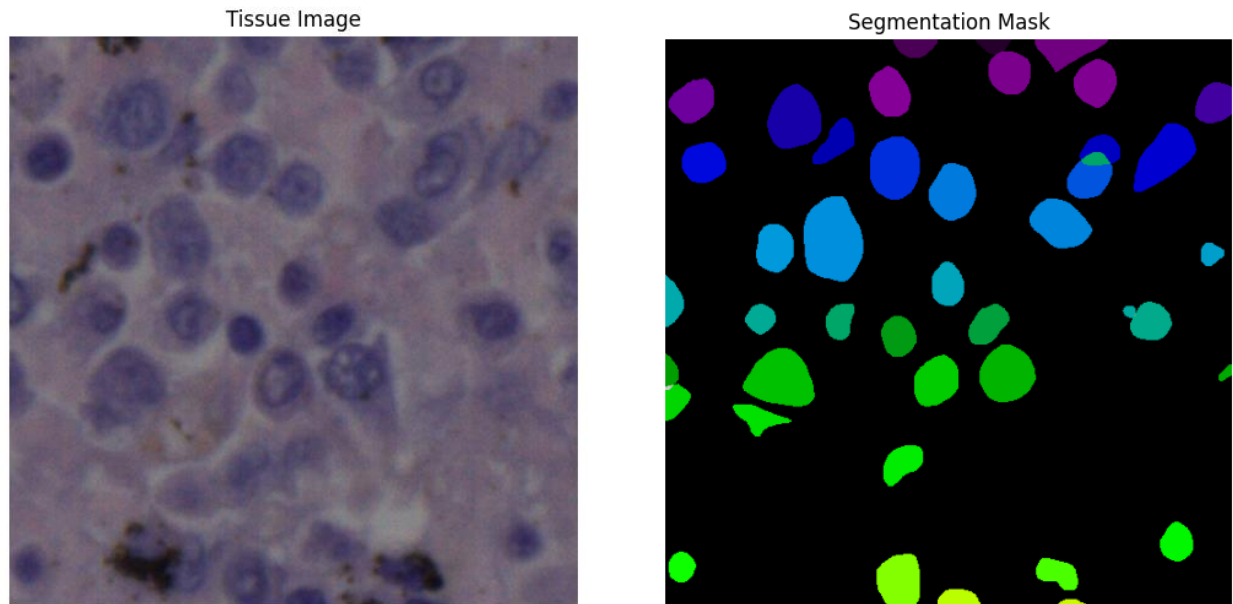


Figure 02: Tissue images and the corresponding segmentation mask sample

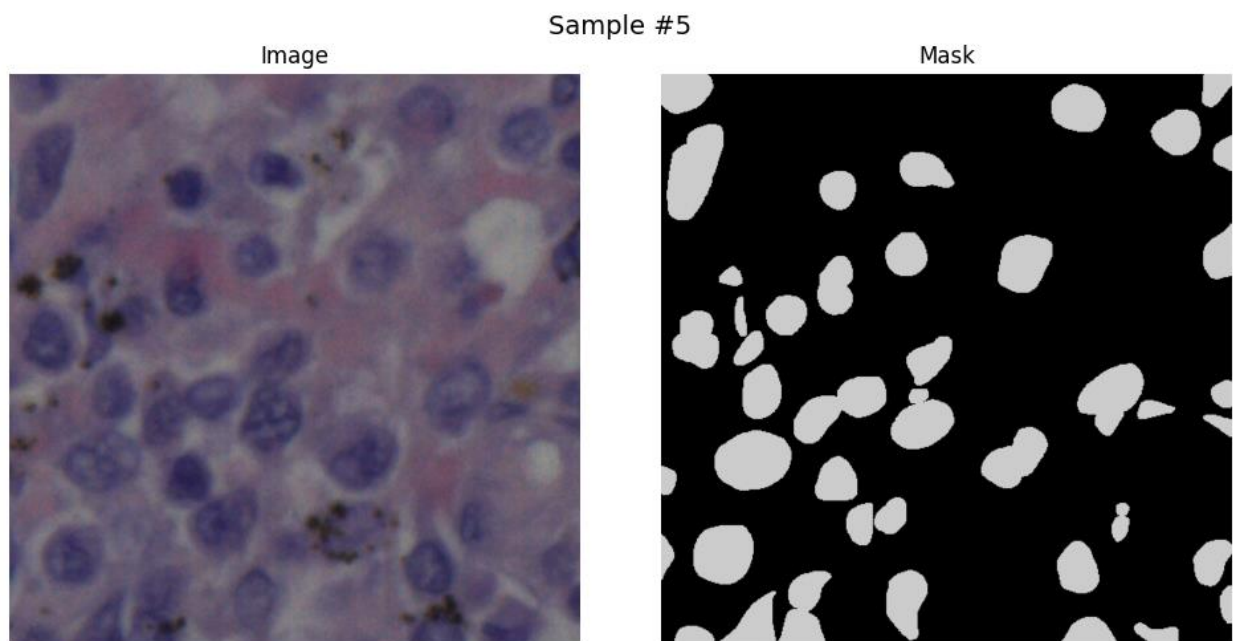


Figure 03: Image and mask pair sample

## 3 Model Architecture and Implementation

### 3.1 MobileSAM

MobileSAM is a lightweight version of the Segment Anything Model (SAM) optimized for resource-constrained devices. It preserves core components of SAM such as the image encoder and mask decoder while reducing model size significantly.

### 3.2 LoRA Integration

LoRA introduces trainable low-rank matrices to the attention layers of the image encoder and prompt encoder without modifying original weights directly. This drastically reduces the number of tunable parameters.

**Network Diagram:** Figure 02 shows how LoRA layers are added to the transformer attention blocks of the MobileSAM encoder.

### 3.3 Implementation Details:

Base model: MobileSAM pretrained weights

Fine-tuning method: LoRA with rank = 4, alpha = 16

Modified layers: Self-attention layers of the image encoder

Frozen parameters: All SAM weights except LoRA adapters

**Training with 5-Fold Cross-Validation:** The training process employed a 5-fold cross-validation strategy to evaluate the generalization performance of the MobileSAM model fine-tuned with LoRA. Each fold was trained for 30 epochs using the AdamW optimizer with a learning rate of 0.0001 and a batch size of 4. To optimize segmentation performance, a composite loss function combining Dice Loss and Cross Entropy Loss was used. A step-based learning rate scheduler (StepLR) was applied to adjust the learning rate during training, and mixed precision training was enabled using torch.cuda.amp to accelerate computation and reduce memory usage. The best-performing model in each fold was selected based on the highest validation Dice score.

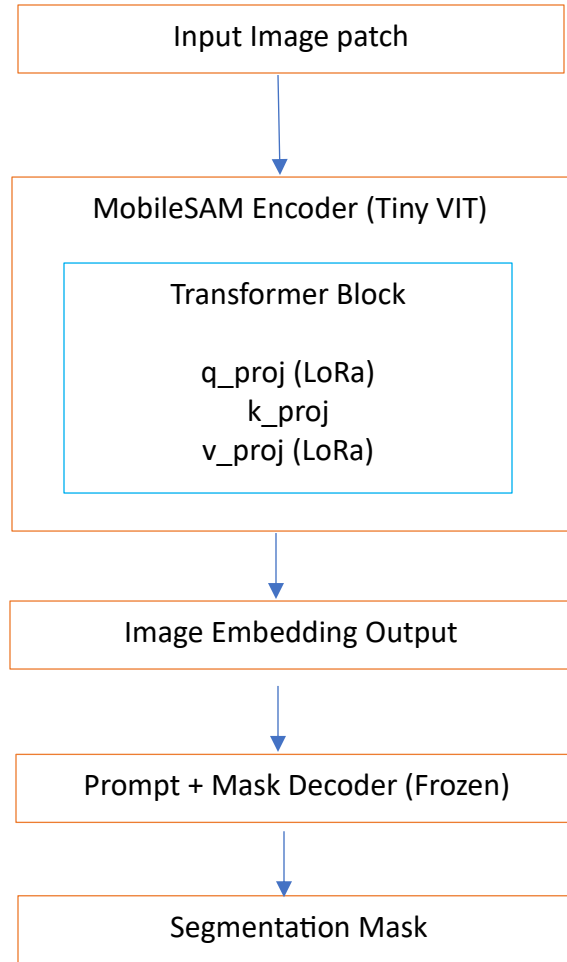


Figure 04: High-level overview of the architecture and layer

## 4 Result and Evaluation

**Number of Tunable Parameters:** Compared to full model fine-tuning (87M parameters), LoRA tuning required only 2.1M tunable parameters, significantly reducing memory and computational load.

Table 01: Segmentation benchmark result based on five-fold cross validation

Model	#Parameters	Avg. Dice (%)	Avg. AJI (%)	Avg. PQ (%)
Shallow U-Net	1.9 million	78.8	50.5	42.7
Deep U-Net	7.7 million	79.7	49.4	40.4
Attention U-Net	2.3 million	80.5	45.7	36.4
Residual Attention U-Net	2.4 million	81.4	46.2	36.9
Two-stage U-Net	3.9 million	76.6	52.8	47.2
Dual Decoder U-Net	3.5 million	79.4	55.9	51.3
This Project	2.1 million	67.4	42.3	39.8

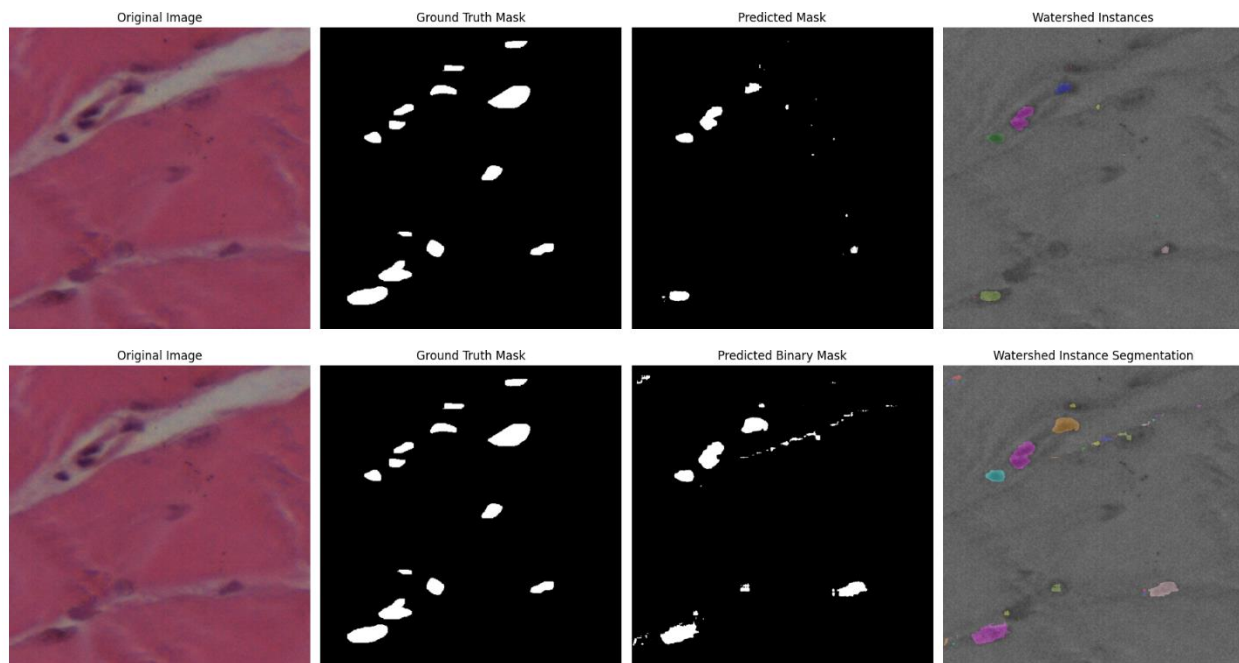


Figure 05: Comparison after 5-epoch and 10-epoch with 5-fold cross validation

**Evaluation:** Evaluation for each fold was conducted using three key metrics aligned with the NuInsSeg paper: Dice Score, AJI (Aggregated Jaccard Index), and PQ (Panoptic Quality). The Dice Score quantifies the overlap between the predicted segmentation masks and the ground truth, serving as a primary measure of segmentation accuracy. AJI extends the traditional Jaccard Index by accounting for instance-level separation errors, making it particularly suitable for evaluating nuclei instance segmentation. PQ provides a comprehensive assessment by combining both segmentation and detection quality into a single unified metric, offering insights into the overall performance of the model in distinguishing and accurately segmenting individual nuclei.

## 5 Conclusion and Future Work

This work demonstrates the success of parameter-efficient fine-tuning using LoRA on MobileSAM for instance segmentation of nuclei. The approach provides competitive performance with a small fraction of tunable parameters, enabling deployment of modest hardware. This was executed on Google Colab notebook, using the T4 GPU and 16 GB RAM. For future work, other SAM variants, such as EfficientSAM, TinySAM could be explored, and more experiments can be conducted with different LoRA ranks and loss functions.

The code and dataset of this project implementation is available publicly at: <https://github.com/sanjeda-sara/Parameter-Efficient-Fine-tuning-Foundation-Model-for-Nuclei-Instance-Segmentation>

## References

1. NuInsSeg Dataset: <https://doi.org/10.48550/arXiv.2403.01893>
2. GitHub Code for Dataset Prep: <https://github.com/masih4/NuInsSeg>
3. Segment Anything Model: <https://github.com/facebookresearch/segment-anything>
4. MobileSAM: <https://github.com/ChaoningZhang/MobileSAM>
5. LoRA: <https://arxiv.org/abs/2106.09685>
6. Project-Code: <https://github.com/sanjeda-sara/Parameter-Efficient-Fine-tuning-Foundation-Model-for-Nuclei-Instance-Segmentation>