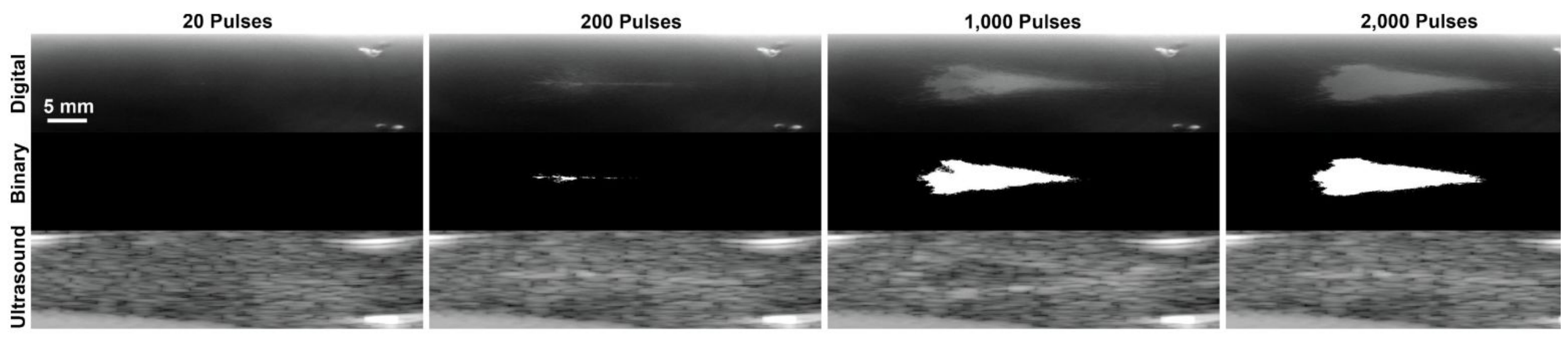
# Ultrasound Image Segmentation *of* Histotripsy Ablation Using DeepLabV3 with Combined Dice-Focal Loss


Shreyans Jain, Soham Gaonkar, Aditya Borate, Mihir Agarwal, Muskan Singh,Prof. Kenneth B. Bader, and Prof.Himanshu Shekhar

Discipline of Electrical Engineering, Indian Institute of Technology Gandhinagar, Gujarat, India
shreyans.jain@iitgn.ac.in, 23110314@iitgn.ac.in , 23110065@iitgn.ac.in
agarwalmihir@iitgn.ac.in, himanshu.shekhar@iitgn.ac.in


## Background and Motivation



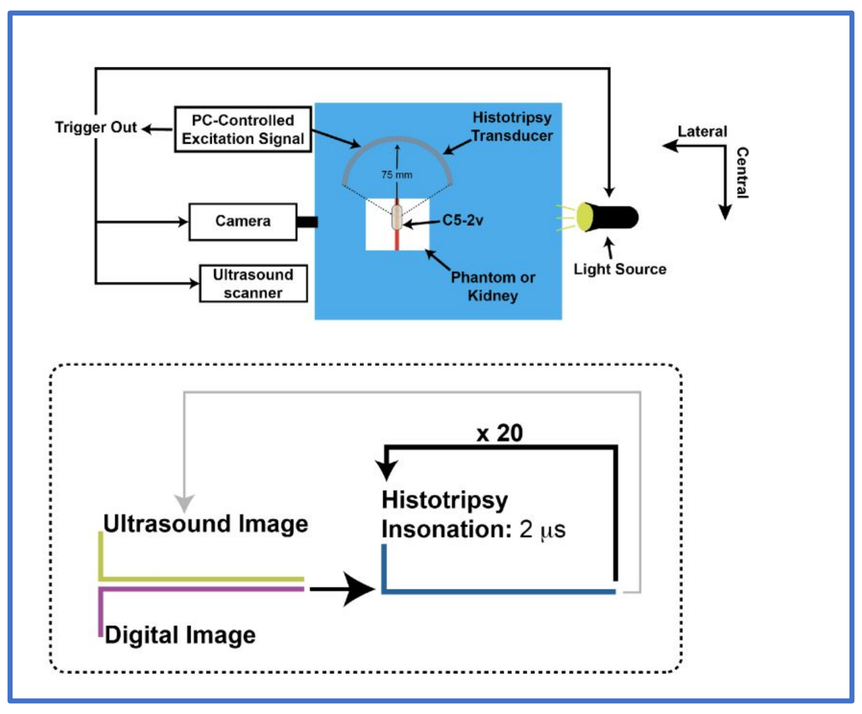

- Histotripsy uses high-amplitude ultrasound pulses to ablate tissue without heat or incisions.
- Ultrasound imaging allows for real-time and safe monitoring of the treatment.
- Current imaging lacks real-time ablation feedback.
- MRI/CT are slow & costly for intra-op use.
- We propose a segmentation approach based on DeepLabV3, incorporating Dice-Focal loss to accurately identify ablated regions.
- Our goal is to enable real-time assessment of ablation using ultrasound imaging alone.

## Methodology

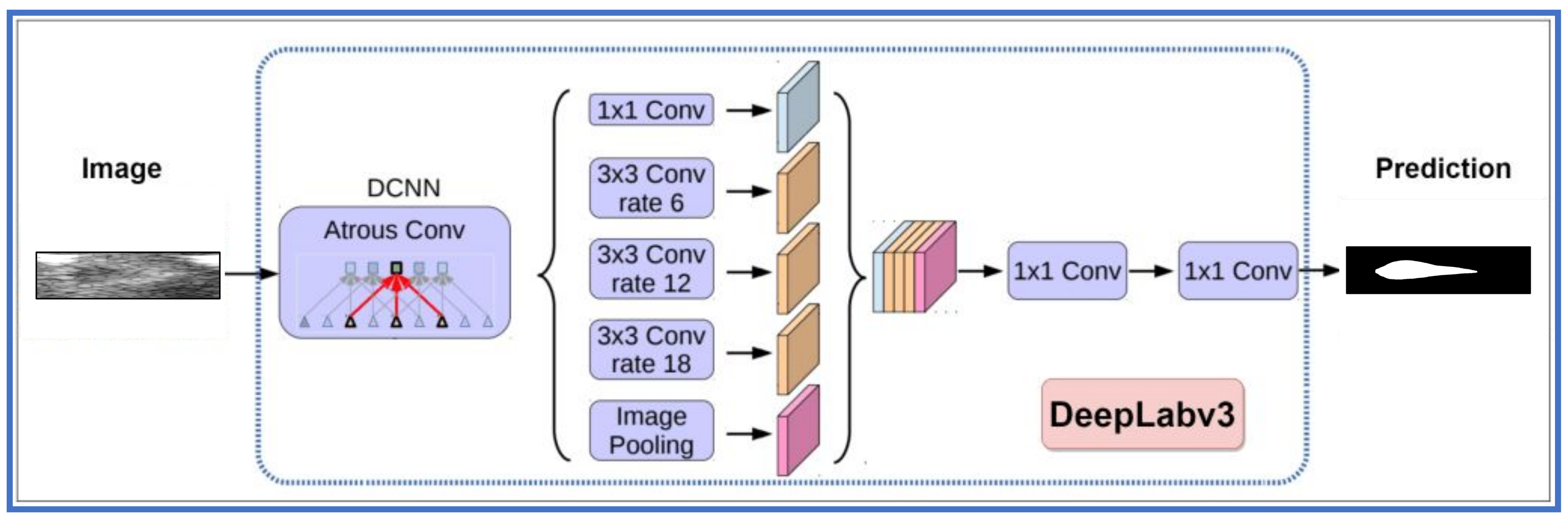
Data Acquisition → Data Annotation → Preprocessing and Augmentation → Supervised Learning → Evaluation

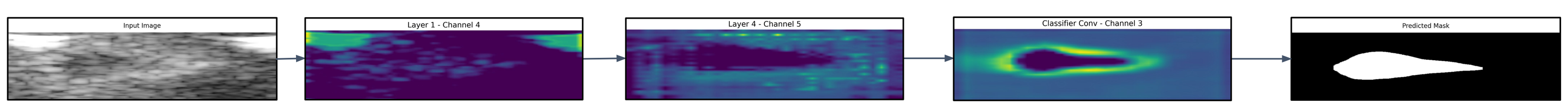
## Experimental Setup

- B-mode ultrasound images were collected during histotripsy experiments in collaboration with UChicago Radiology, using agarose phantoms and ex vivo porcine kidneys.[1]
- Used 1 MHz, 35 MPa, 20 µs pulses @ 50 Hz Ground truth ablation regions were annotated using co-registered digital images.
- 6 datasets → 880 train | 400 test | holdout set
- The unsupervised data was obtained from Vishwas Trivedi, a PhD student at IIT Gandhinagar.

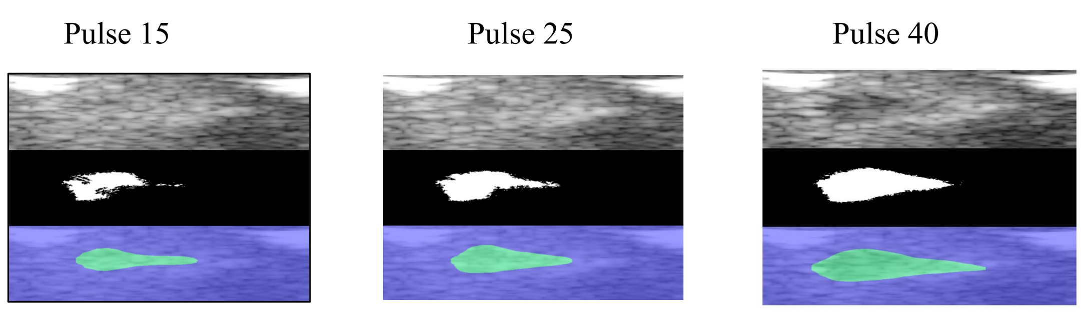



## Approach



- Initialized DeepLabV3 (ResNet101), trained from scratch in a fully supervised setting.[2]
- Early-pulse frames exhibit sparse, low-contrast bubbles, complicating segmentation. We applied oversampling to increase model robustness on these cases.




## Loss and Evaluation Metrics

- **Dice + Focal Loss (Ours):**

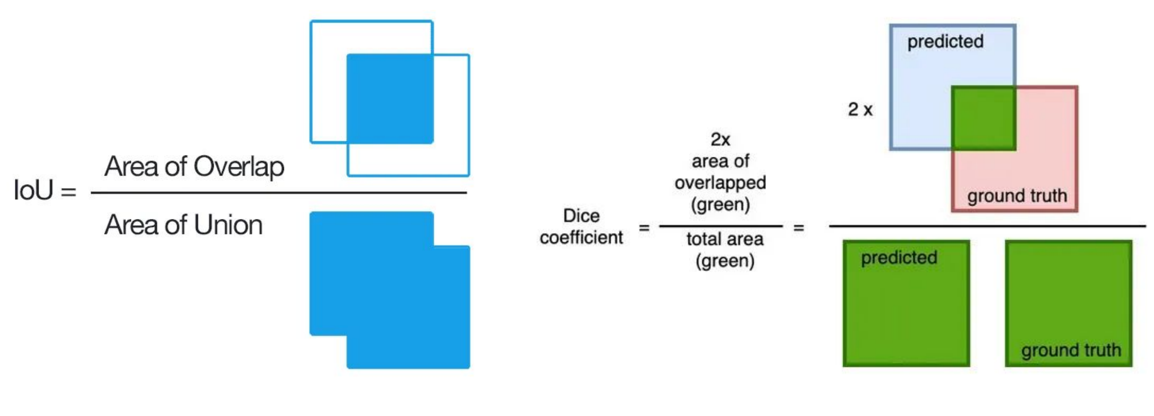
Combined Dice and Focal Loss to handle class imbalance and enhance boundary precision. Dice maximizes overlap in sparse masks, while Focal emphasizes hard-to-classify pixels.

$$\mathrm{DiceLoss}(y,\hat{p}) = 1 - \frac{(2y\hat{p}+\varepsilon)}{y+\hat{p}+\varepsilon} \qquad \mathrm{FocalLoss}(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t)$$

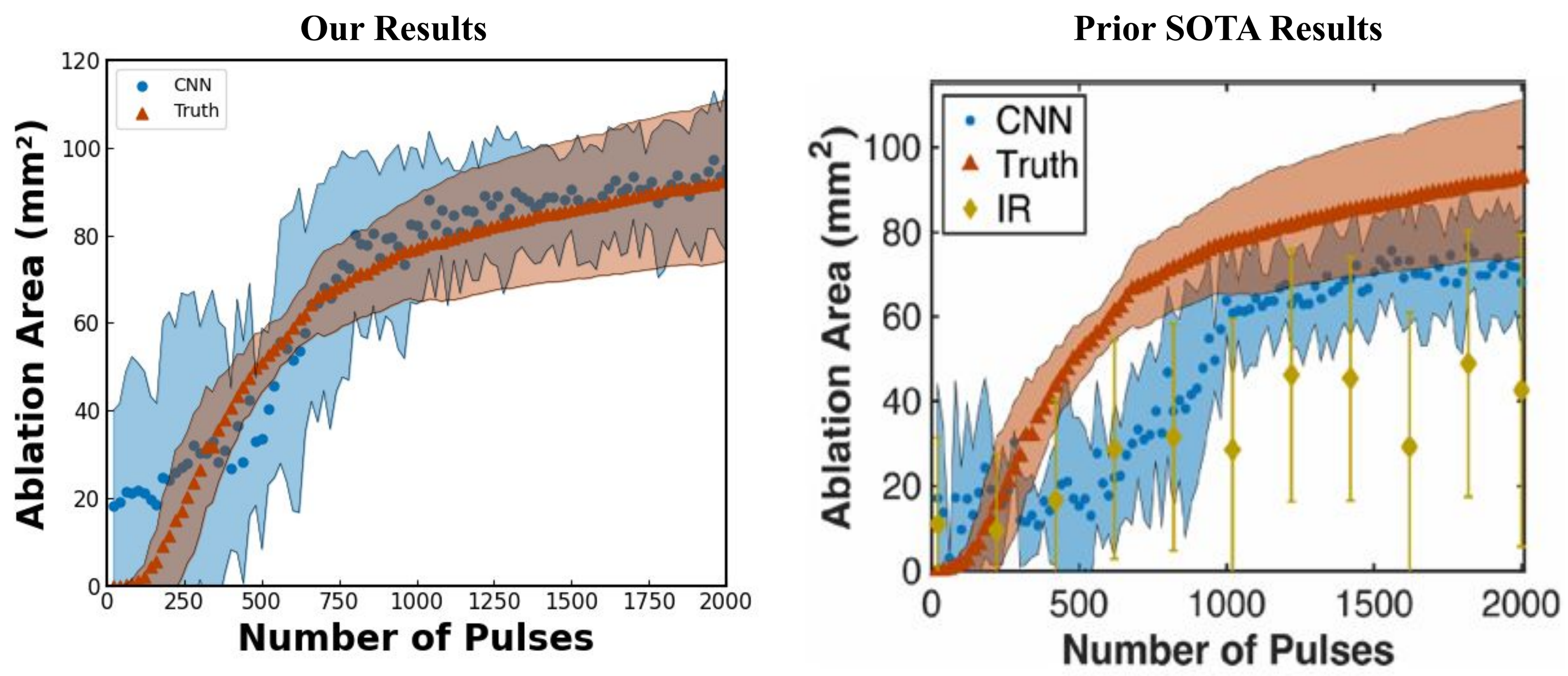
$$\boxed{\mathcal{L}_{\text{Total}} = \lambda_{\text{Dice}}\cdot\mathcal{L}_{\text{Dice}} + \lambda_{\text{Focal}}\cdot\mathcal{L}_{\text{Focal}}}$$

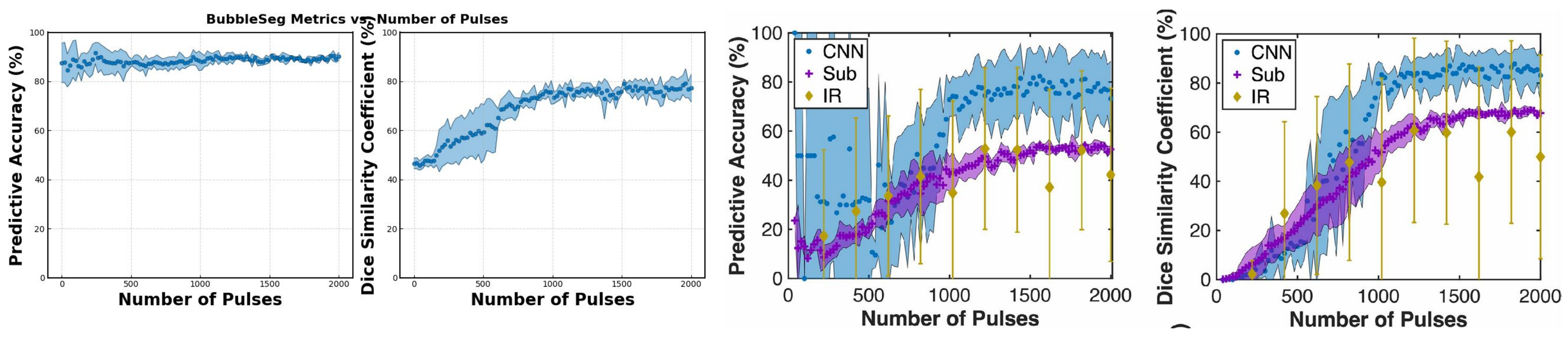
- **Metrics :**

We evaluate using IoU, Dice, and Ablation Area to assess segmentation accuracy, overlap quality, and bubble region quantification.




## Results

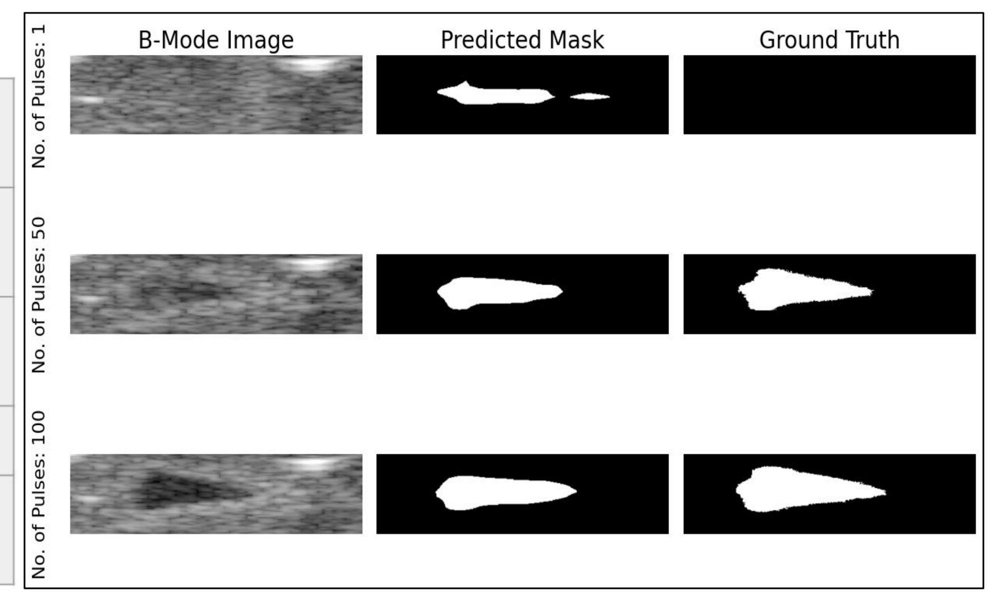



**Metric Comparison**

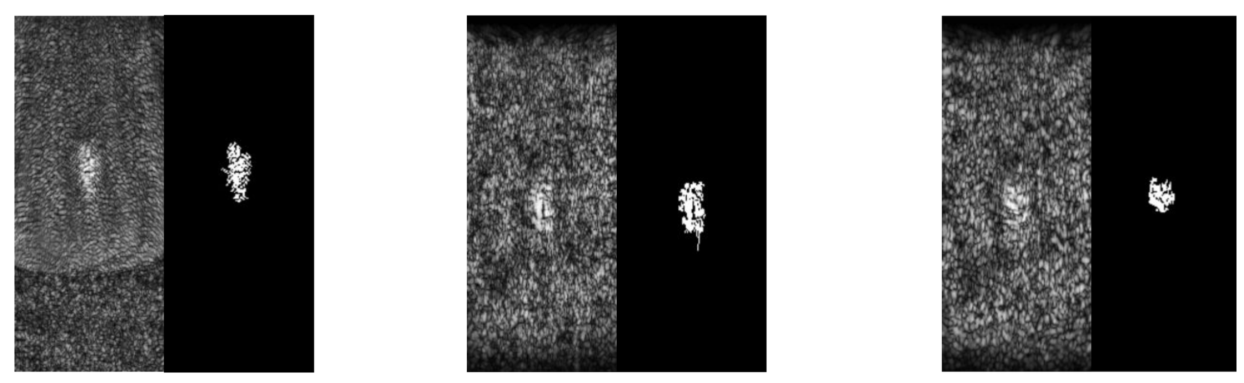
| Metrics | Our Results | Prior SOTA Results |
|---|---|---|
| Global Accuracy | 0.97525 | 0.95555 |
| Mean Accuracy | 0.90524 | 0.80954 |
| Mean IOU | 0.82537 | 0.76461 |
| Weighted IOU | 0.95525 | 0.91648 |

**Visualizations of Predictions**




## Unsupervised Learning

- Segmenting bubble clouds using from unlabeled histotripsy ultrasound data using CCA (Connected Component Analysis) :



Frame 0 Frame 25 Frame 50

- **Synthetic Data Generation :**
Simulated bubble shapes using custom generation function which involves Gaussian Blur for smoothness , striated + reverberation patterns , depth attenuation and realistic speckle noise.

## Challenges Faced

- Ground truth annotations by radiologists tend to overestimate ablation regions.
This can cause evaluation metrics to undervalue model predictions, even when they are more accurate.
- Sparse or small bubble regions (initial pulses) are harder to segment, leading to more false positives.
- Annotated data for histotripsy is scarce, expensive, and challenging to acquire.
These factors make large-scale, high-quality supervised training difficult.

## Summary and Future Work

- Presented a DeepLabV3-based model with Dice-Focal loss for accurate ablation segmentation
- Achieves expert-level performance on ultrasound B-mode images

**Future Work:**

- Improve early-pulse segmentation using curriculum learning
- Integrate attention and adaptive loss strategies
- Explore unsupervised learning for better generalization with limited labels

## References


1. Miao K, Basterrechea KF, Hernandez SL, Ahmed OS, Patel MV, Bader KB. Development of Convolutional Neural Network to Segment Ultrasound Images of Histotripsy Ablation. IEEE Trans Biomed Eng. 2024 Jun;71(6):1789-1797. doi: 10.1109/TBME.2024.3352538. Epub 2024 May 20. PMID: 38198256.
2. Chen, L., Papandreou, G., Schroff, F., & Adam, H. (2017). Rethinking Atrous Convolution for Semantic Image Segmentation. ArXiv. https://arxiv.org/abs/1706.05587