Patch Based CNN for Gland Instance Segmentation (Optimization of NNs)

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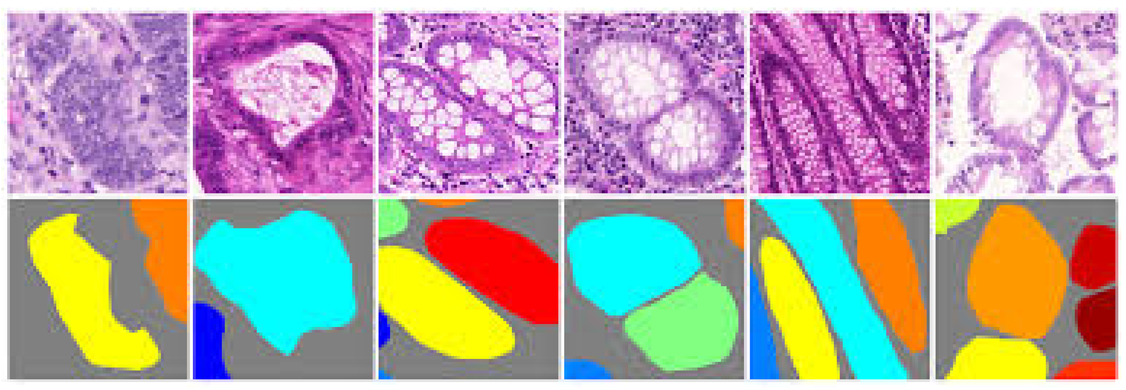
1. Introduction

With the advent of machine learning methods, need for automated medical image analysis also aroused. in these applications, hardware implementation is often needed but resources are limited and images are typically large. We focus on instance segmentation task by patch based CNNs instead of image based approaches to tackle the memory challenge.

2. Dataset

We use the 2015-Gland Segmentation Challenge [1] which consists of 85 images for training and 60 for test.
Challenges of dataset for instance segmentation:
- Dissimilar gland Shapes
- Small borders between some glands
- misclassification of lumen and white tissue



3. Patch Based

- Segments smaller patches independently
- Some global information are overlooked
- More data, but imbalanced...
- Additional augmentation opportunities
- limited number of training images

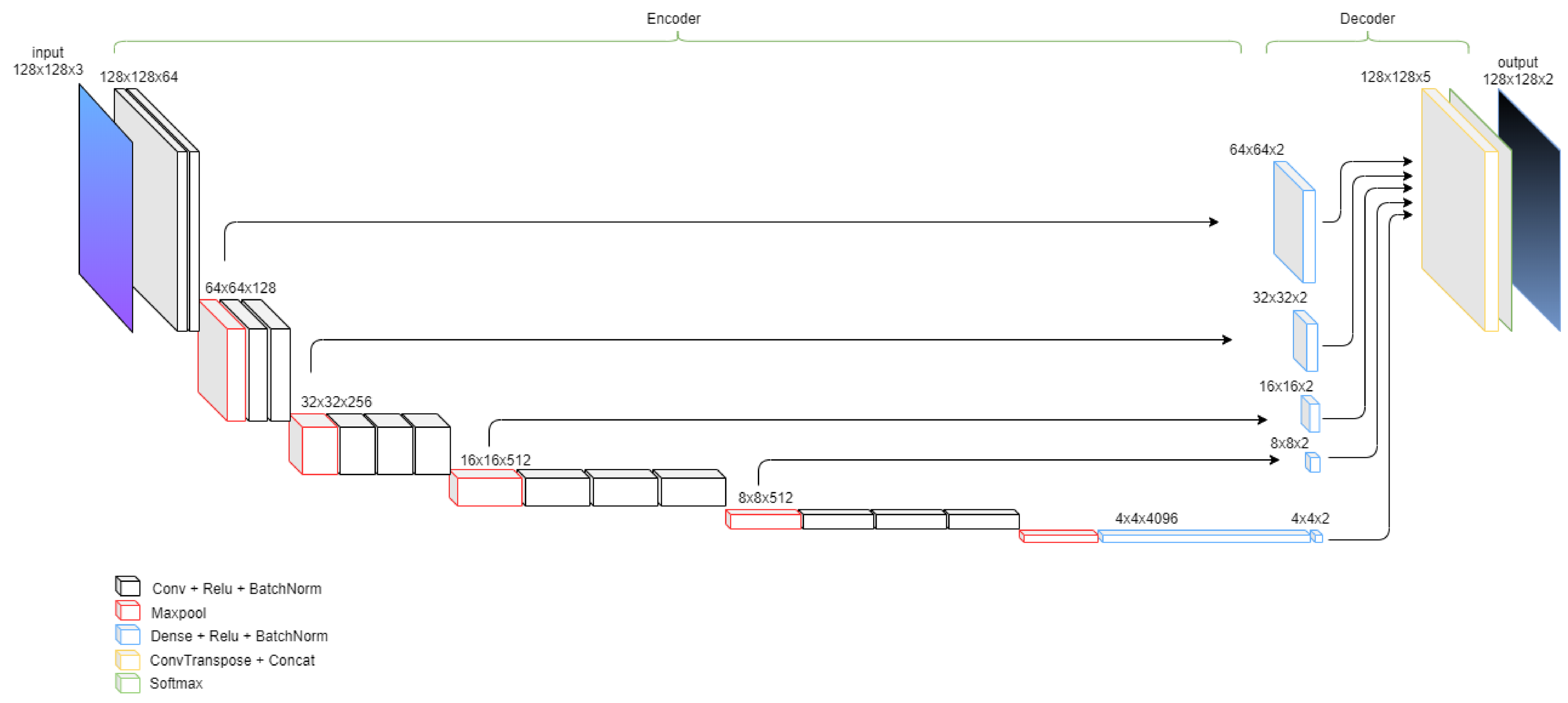
Metrics:

$$DiceScore = \frac{2xTP}{(TP+FP)+(TP+FN)}$$

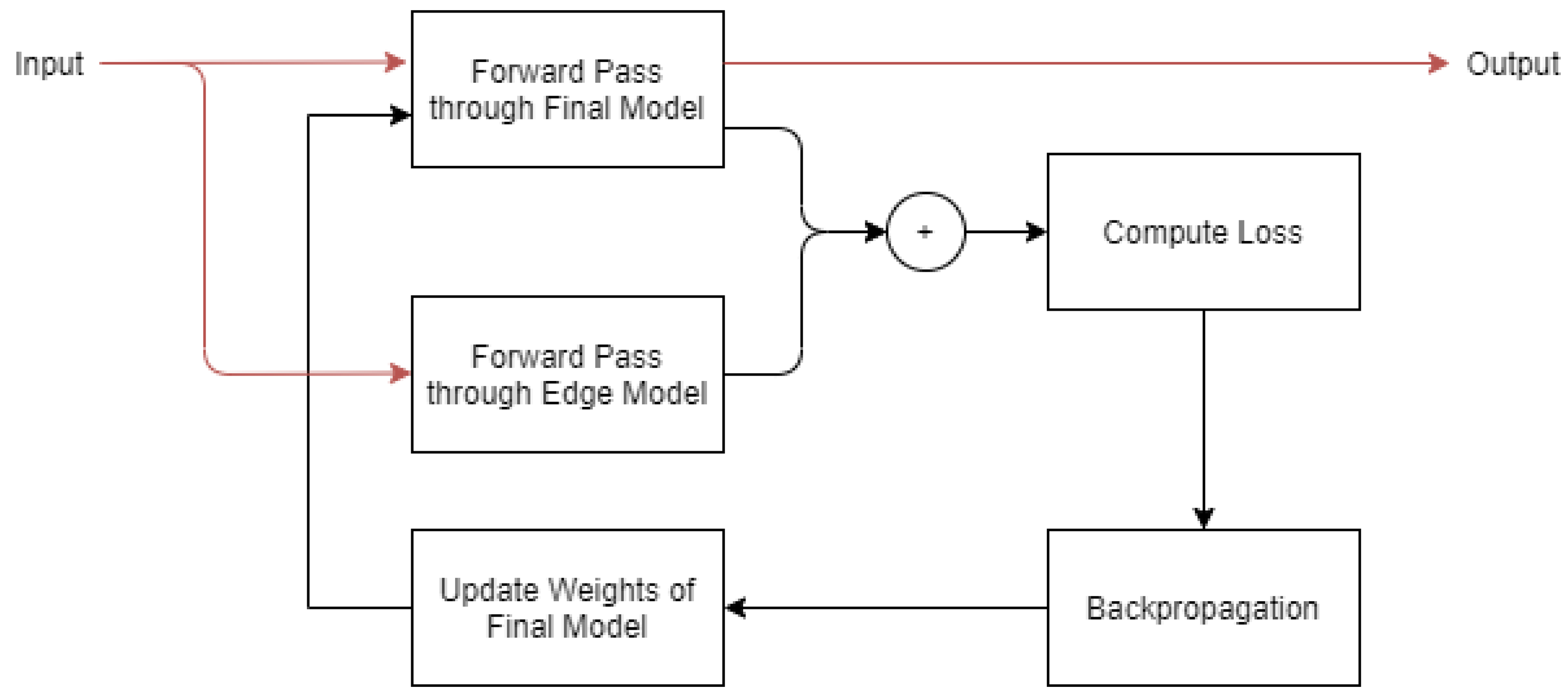
$$D_{object}(G,I) = \frac{1}{2}(\sum_{i=1}^{n_I} W_i D(G_i, I_i + \sum_{j}^{n_G} \tilde{W}_J D(\tilde{G}_J, \tilde{G}_J)$$

4. Models

Most segmentation approaches consist of an encoder and a decoder part. The proposed model is inspired by FCN [2], and makes use of and fine tunes pretrained VGG-16 weights [3] in its encoder.



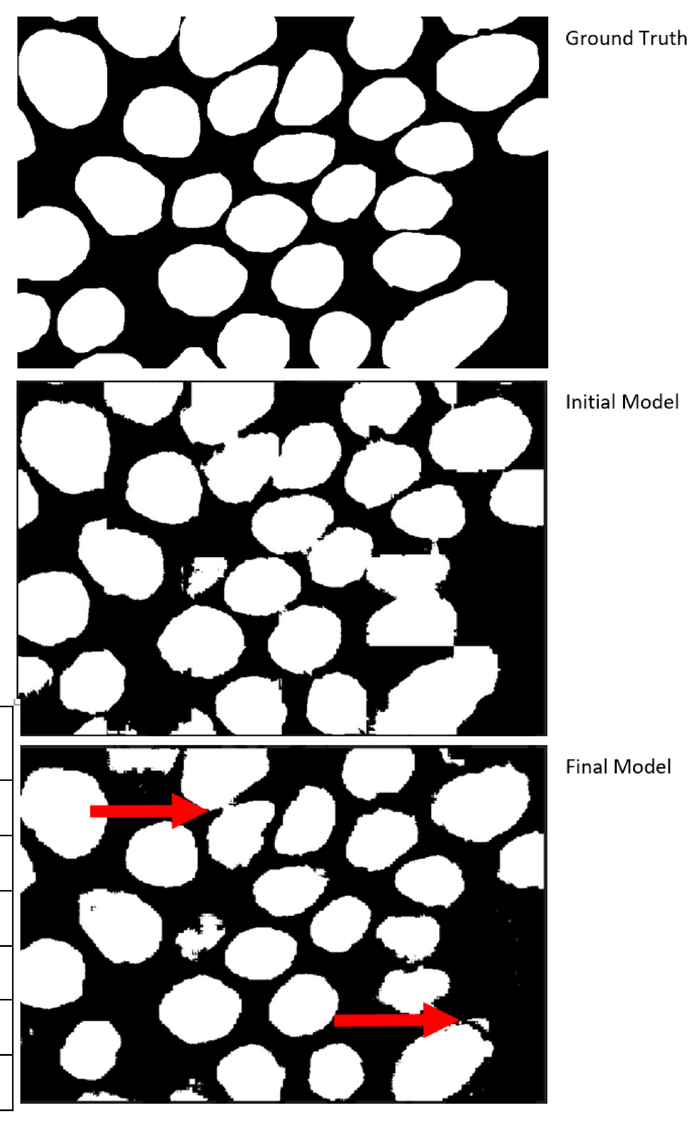
The model (Initial Model) is trained to detect glands. Furthermore, another model (Edge Model) is trained to detect the edges using the predicted glands, especially ones that are corrupted or missed. Then, the initial model called Final Model is now additionally fine tuned with a new loss function in which the edge model predictions are added to the final model predictions to better differentiate separate glands.



5. Results

Initial tests showed prominence of patch based method over image based in terms of dice. Further improvements yielded a better dice score than other purposed methods such as S. Rezaei[4] or CUMedVision2[5] which was the state of art, However, because of time constraints, not enough experiments were conducted for bettering object dice and it is yet to reach the other methods.

	Initial Dice(F1)	Dice(F1)	Object Dice
Image Based (384x512)	0.9000	-	-
Patch Based (256x256)	0.8831	-	-
Patch Based (128x128)	**0.9120**	**92.3**	0.788
Patch Based (64x64)	0.8876	-	-
CUMedVision2	-	0.912	**0.897**
S. Rezaei	-	0.868	0.867



6. Conclusion

1. Smaller windows of Gland Segmentation Challenge dataset can contain richer features and patch based methods not only can perform better in terms of F1 score, but also reduce memory requirements drastically.
2. Some edges might require a more global view or a better class balance to be detected, as they are missed by our patch based model.

7. References

[1] Korsuk Sirinukunwattana. Gland segmentation in histology images challenge (glas) dataset.

[2] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. *CoRR*, abs/1411.4038, 2014.

[3] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[4] Wenqi Li, Siyamalan Manivannan, Shazia Akbar, Jianguo Zhang, Emanuele Trucco, and Stephen J. Mckenna. Gland segmentation in colon histology images using hand-crafted features and convolutional neural networks. *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, pages 1405–1408, 2016.

[5] Hao Chen, Xiaojuan Qi, Lequan Yu, and Pheng-Ann Heng. DCAN: deep contour-aware networks for accurate gland segmentation. *CoRR*, abs/1604.02677, 2016.