Micro-Net-508 for gland segmentation in microscopic images

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Project Scope

1) **Reproduce Paper**

No Code Implementations Available

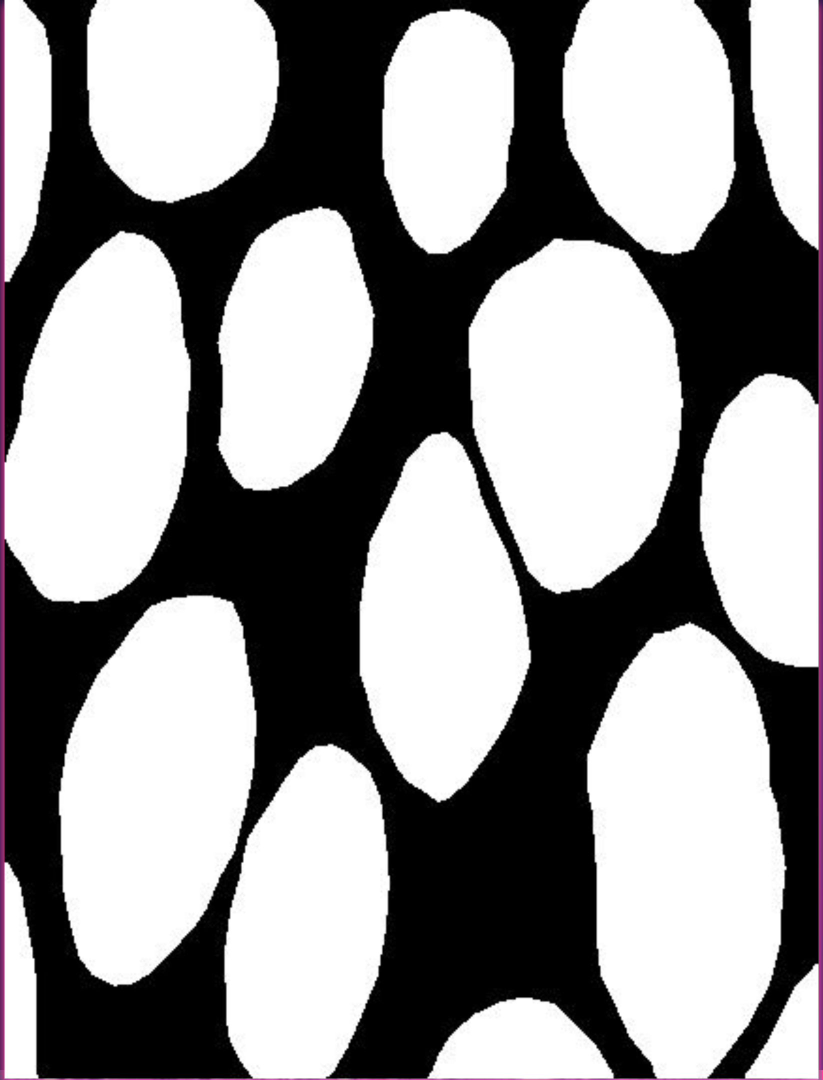
2) Novel Dataset or Task

PyTorch

3) Research

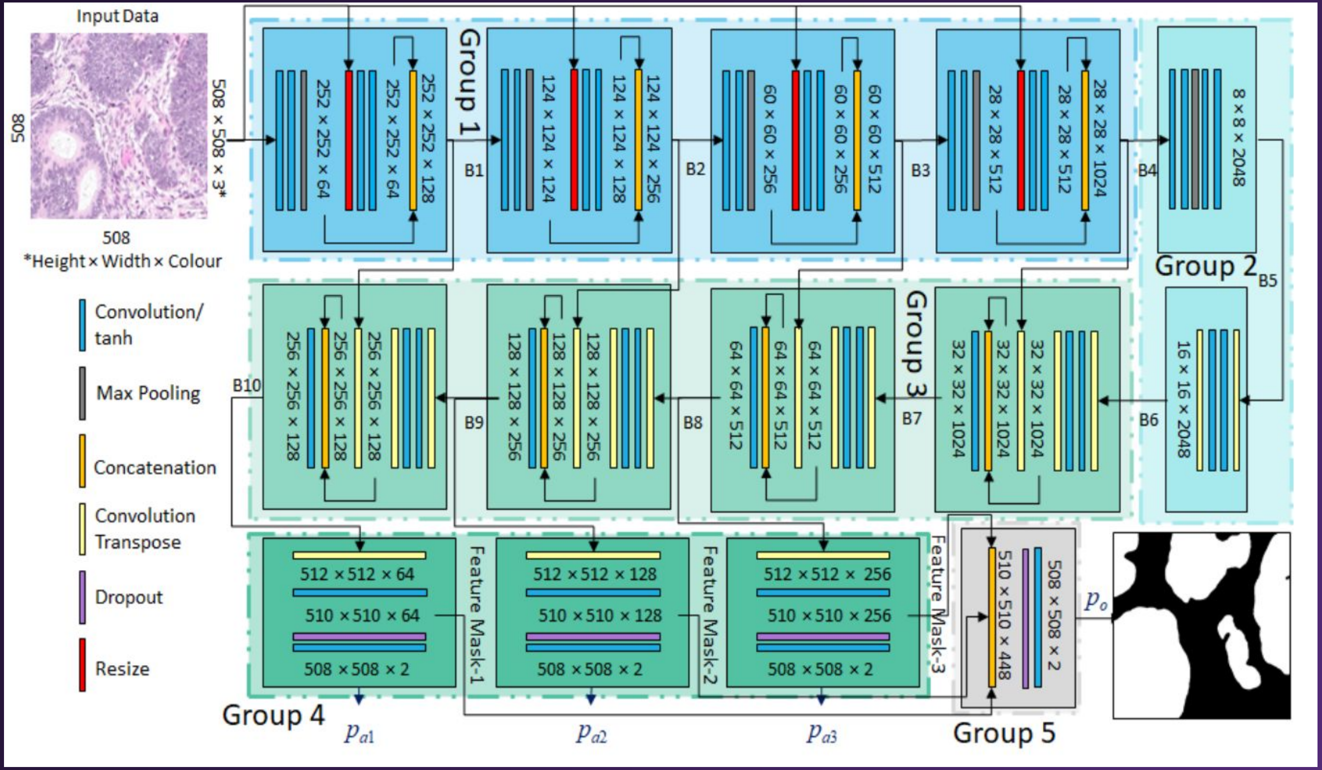
PROBLEM OVERVIEW

– Microscopic Image Segmentation



Paper

Micro-Net: *A unified model for segmentation of various objects in microscopy images [Raza et. al. 2019]*



Proposed Architecture

Key Ideas

Recognizes Variable Cell Types / Sizes

Learns image features at multiple input resolutions for better understanding of tissue components

Retains More Contextual Information

Connects intermediate layers for better localization and context

Bypasses max-pooling through extra layers to retain information from weak features

Implementation Setup

Dataset

- Multiplexed Fluorescence Imaging Data [NOT PUBLIC]
  - Applicable for Micro-Net-252 model
- Computational Precision Medicine (CPM) Data Set for nuclear segmentation [NOT PUBLIC]
  - Applicable for Micro-Net-252 model
- Gland Segmentation (GLaS) Challenge Data Set
  - Only applicable for Micro-Net-508 model

Data Preparation

- Load training examples (85)
- Data Augmentation (2380)
- Create a validation set (90%-10% split)
- Held-out test set (60)

Challenges : Insufficient Data

1 of 3 Datasets public

GLaS dataset: 85 training images

No details about augmentation results

Solution ~ Augmentation

Radial distortions

Flip/Rotation

Gaussian Blur

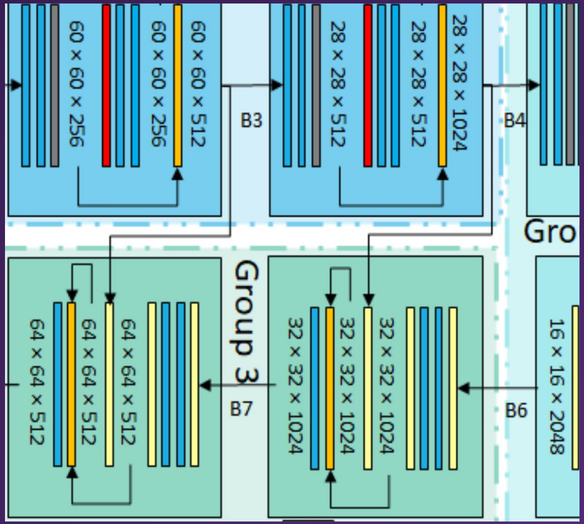
Challenges : Layer Configurations

Dimensions only known for intermediate results after a group of layers

No information on individual CONV, TCONV, POOL layer configurations or outputs within a group

Solution ~

Debugging for tensor dimensions after each layer



Challenges : GPU Memory Constraints

- Runtime crash on Google Colab [Paid] for the given training example size of 508x508x3

- Debugging in progress

Possible Solutions ~

Gradient Accumulation

Free GPU memory

Model Evaluation

For a given image, compare 0 or 1 probabilities between predicted and ground truth images

Compute **F1 score** as:

(2 * precision * recall) / (precision + recall)

where:

```
precision = tp / (tp + fp)
recall = tp / (tp + fn)
```

Final score = **Average** across all images

Method	F1 score			
	Test A		Test B	
	S	R	S	R
Xu et al. (2017)	0.893	4	**0.843**	**1**
Manivannan et al. (2018)	0.892	5	0.801	2
Proposed	**0.913**	**1**	0.724	5
Xu et al. (2016)	0.858	9	0.771	3
CUMedVision2	0.912	2	0.716	7
ExB1	0.891	6	0.703	8
ExB3	0.896	3	0.719	6
Freiburg2	0.870	7	0.695	9
CUMedVision1	0.868	8	0.769	4
ExB2	0.892	5	0.686	10
Freiburg1	0.834	10	0.605	11
CVML	0.652	12	0.541	12
LIB	0.777	11	0.306	14
vision4GlaS	0.635	13	0.527	13

DEMO

Remaining Tasks

Debug Issues

Model Tuning

Paper Write-up

THANKS!