

Deep Learning Methods for Image Segmentation Containing Translucent Overlapped Objects

Tayebbeh Lotfi Mahyari, Richard M. Dansereau

Systems and Computer Engineering, Carleton University

Ottawa, Canada

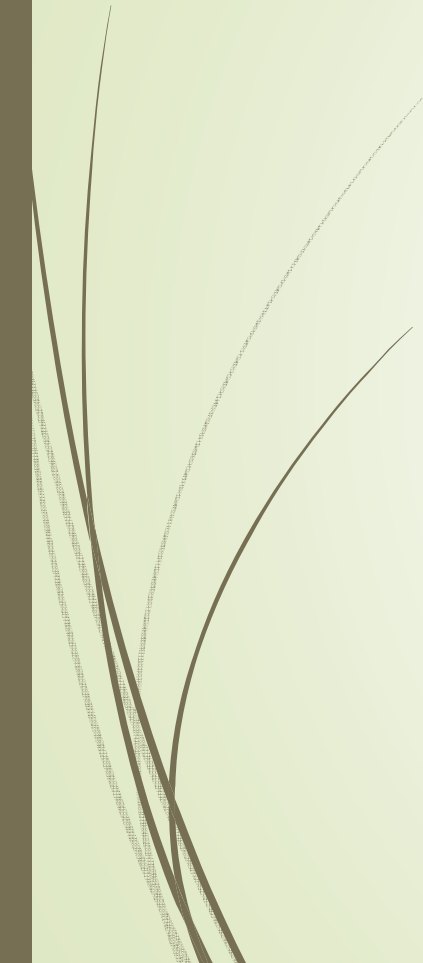


Outline

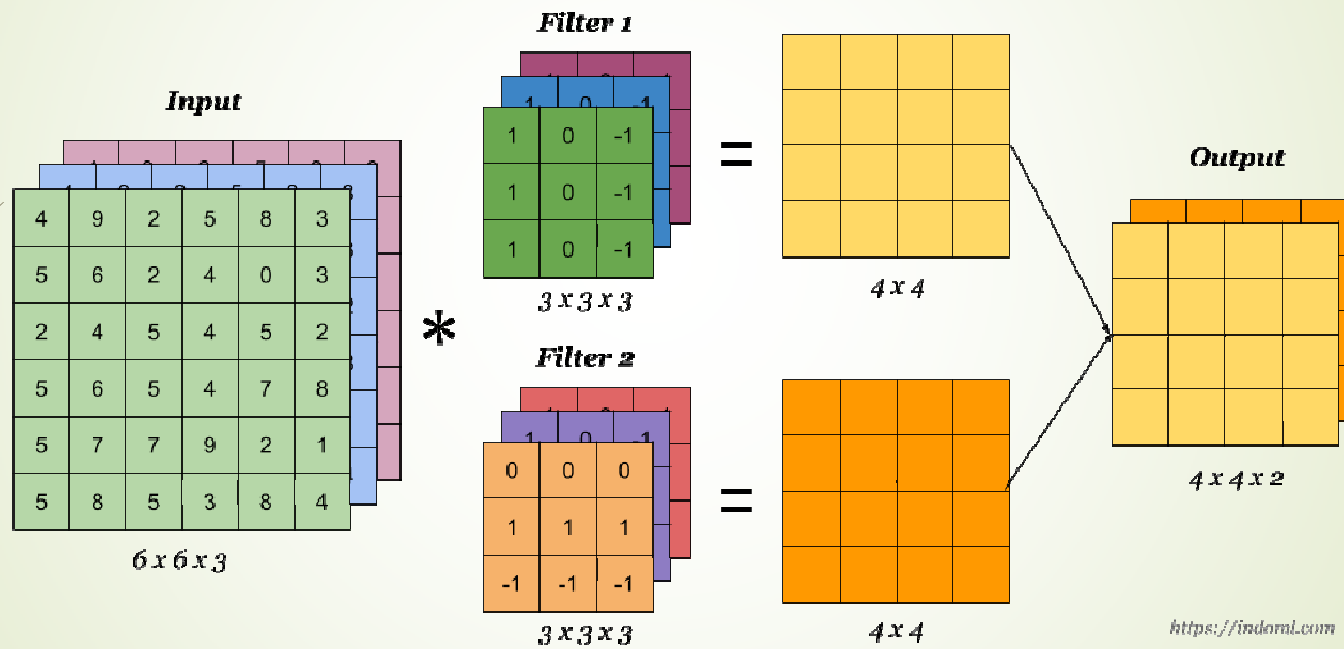
- Convolutional neural networks (CNNs)
- Image classification and image segmentation on CNNs
 - AlexNet, VGGNet, GoogLeNet, ResNet
 - SegNet
- Proposed network
 - Transfer learning
 - Proposed network
 - Proposed residual network
- Results
- Conclusion



Convolutional Neural Networks(CNNs)

- ▶ Deep learning in machine learning (2006)
 - ▶ CNNs
 - ▶ Convolutional layers
 - ▶ Activation layers
 - ▶ Batch normalization layers
 - ▶ Pooling layers
 - ▶ Fully-connected layers
- 

Convolutional Layers



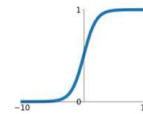
Activation Layers

- ▶ Rectified linear unit
- ▶ Leaky ReLU
- ▶ Tanh
- ▶ Sigmoid
- ▶ Maxout
- ▶ ELU

Activation Functions

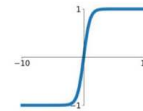
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



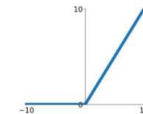
tanh

$$\tanh(x)$$



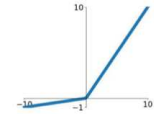
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$



Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Batch Normalization Layers

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\dots m}\}$;

Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

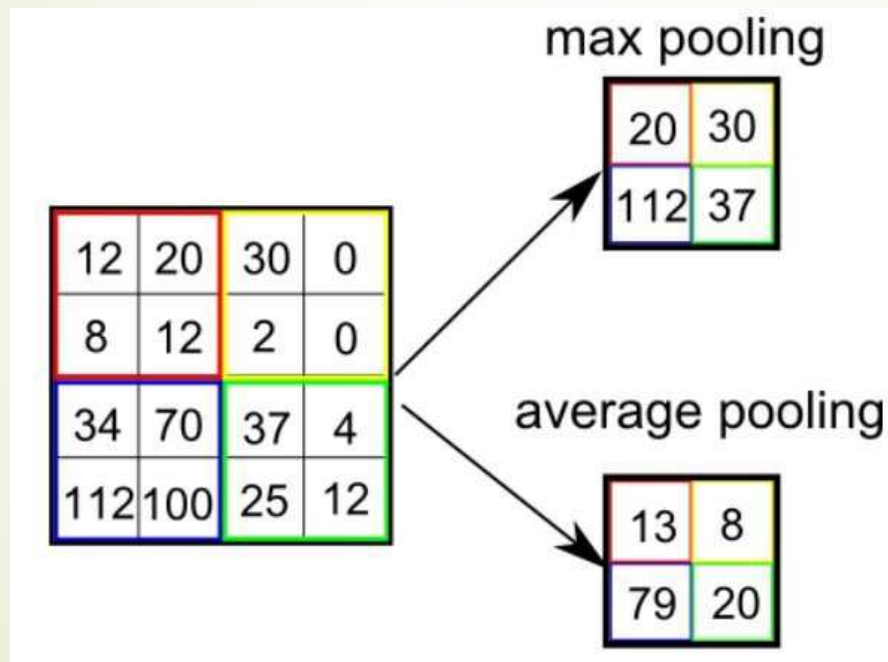
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{ mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{ mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{ normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{ scale and shift}$$

Pooling Layers



Fully-connected Layers

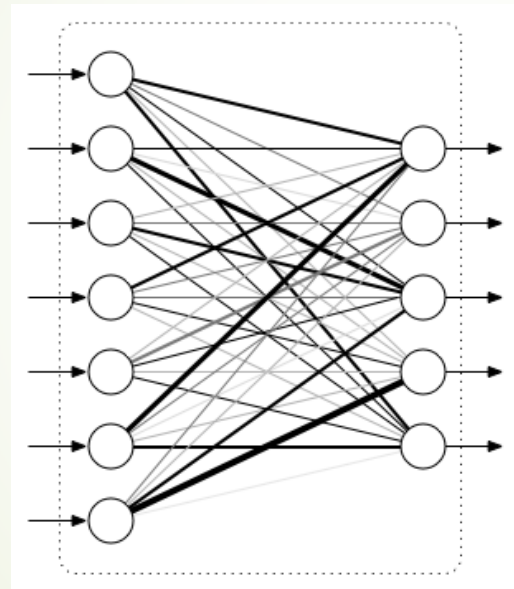
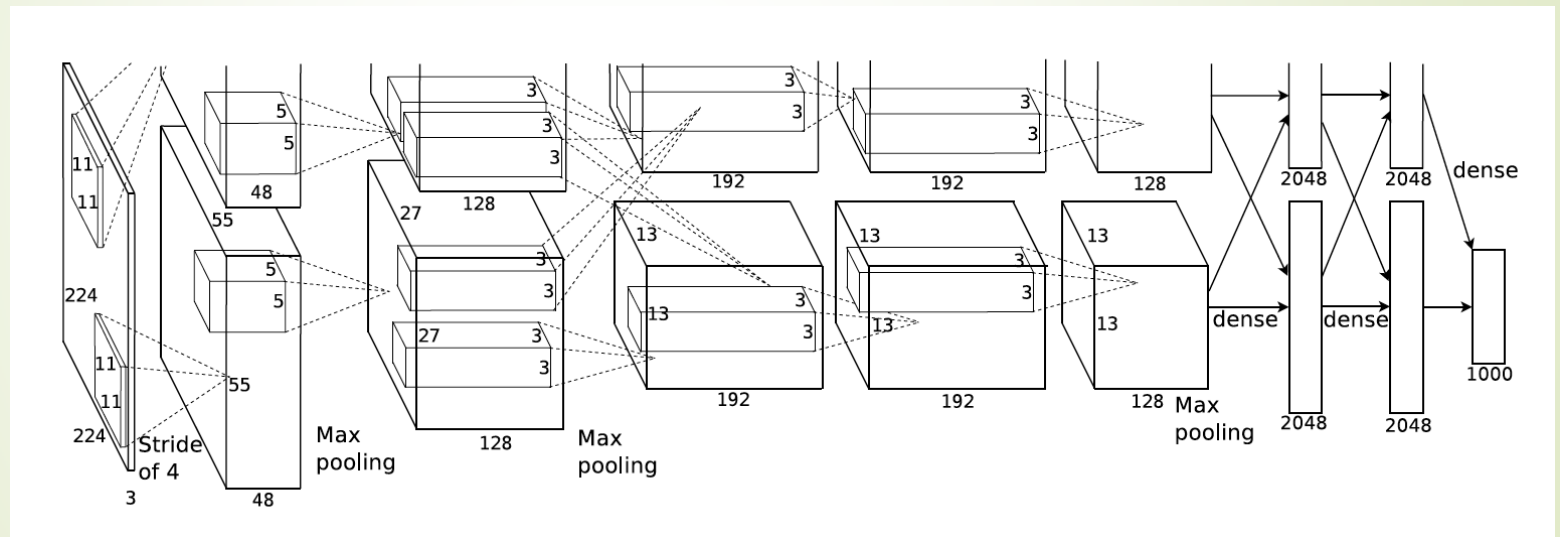




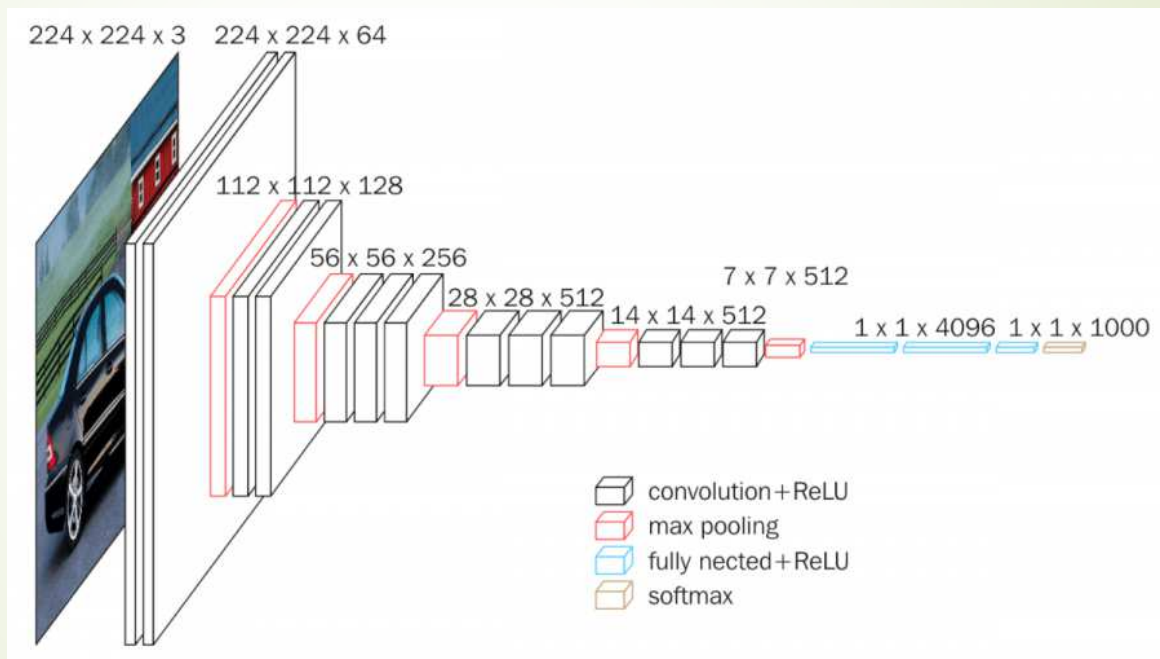
Image Classification & Image Segmentation

- ▶ AlexNet [1]
- ▶ VGGNet [2]
- ▶ GoogLeNet [3]
- ▶ ResNet[4]
- ▶ SegNet [5]

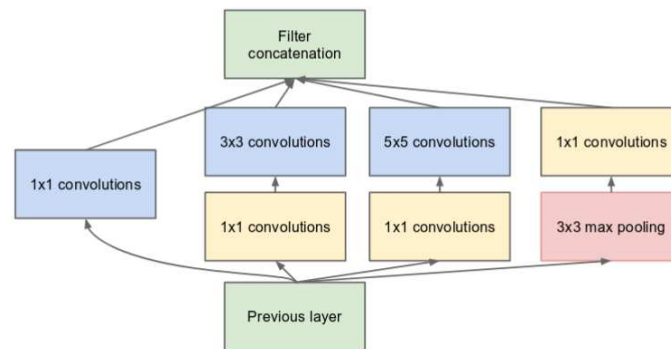
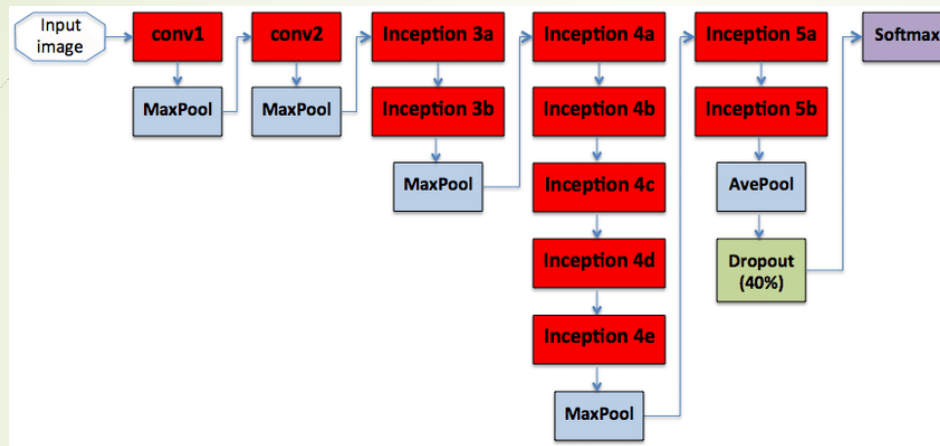
AlexNet



VGGNet

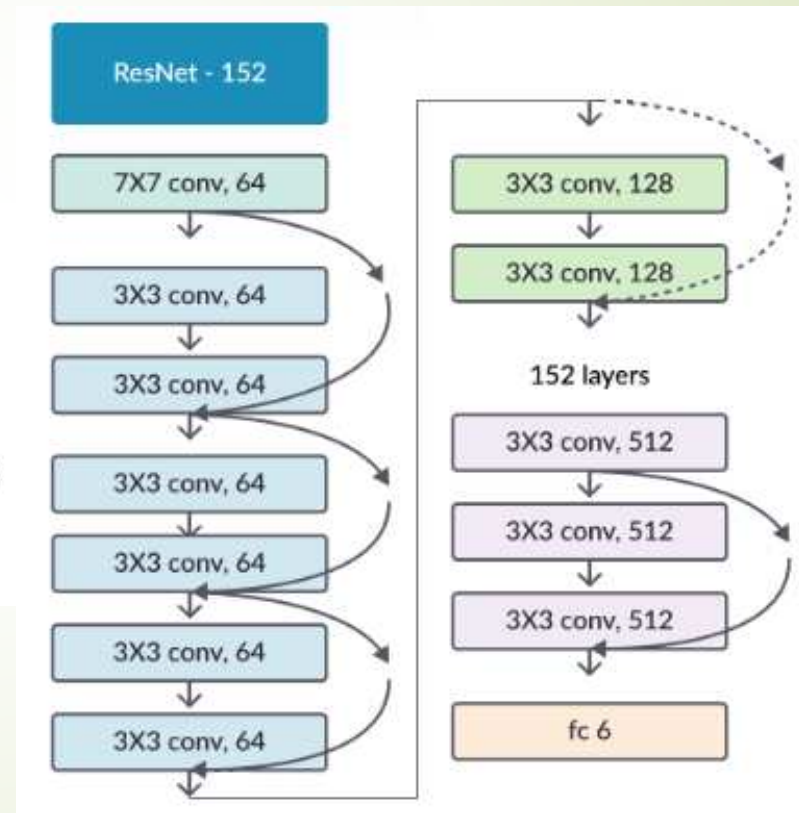
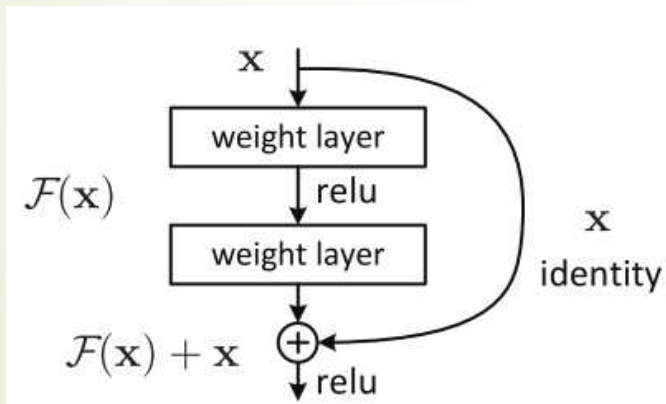


GoogleNet

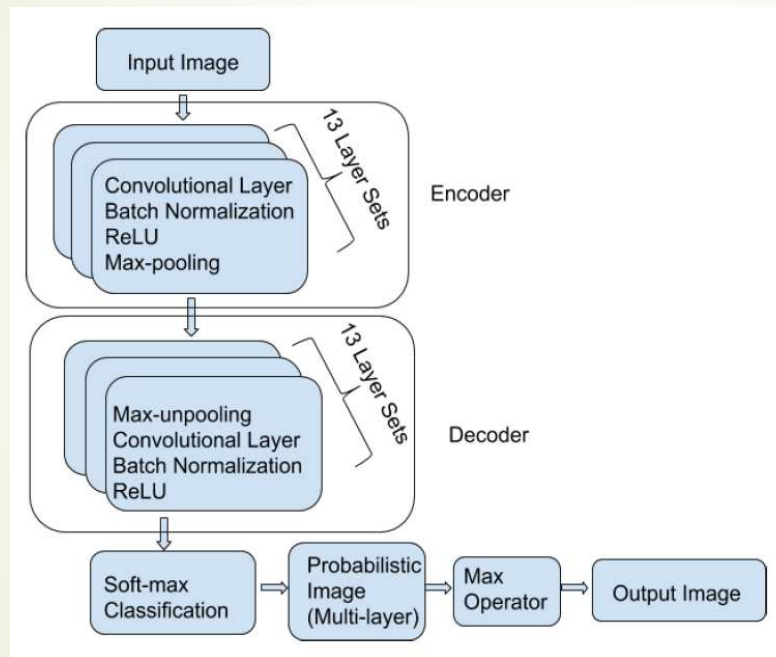


(b) Inception module with dimension reductions

ResNet



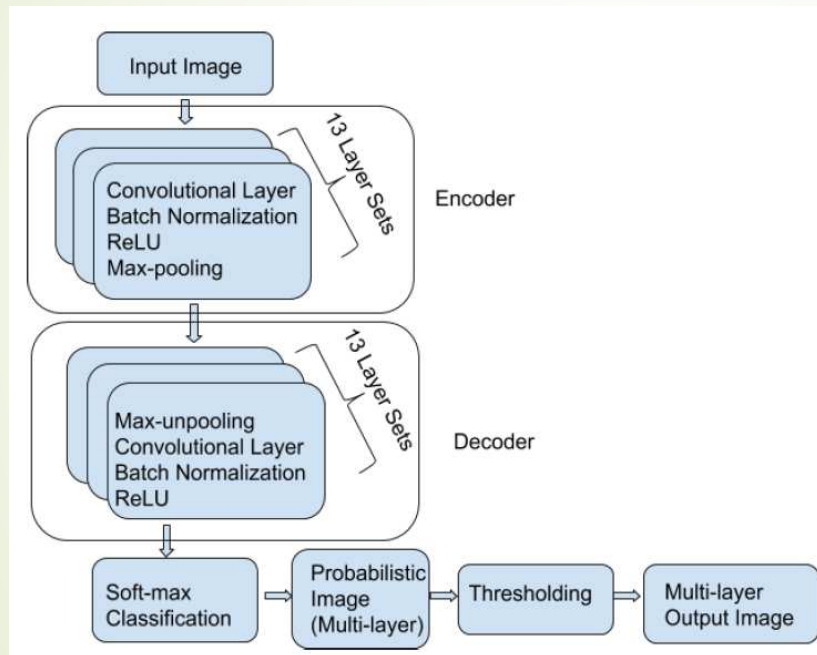
SegNet



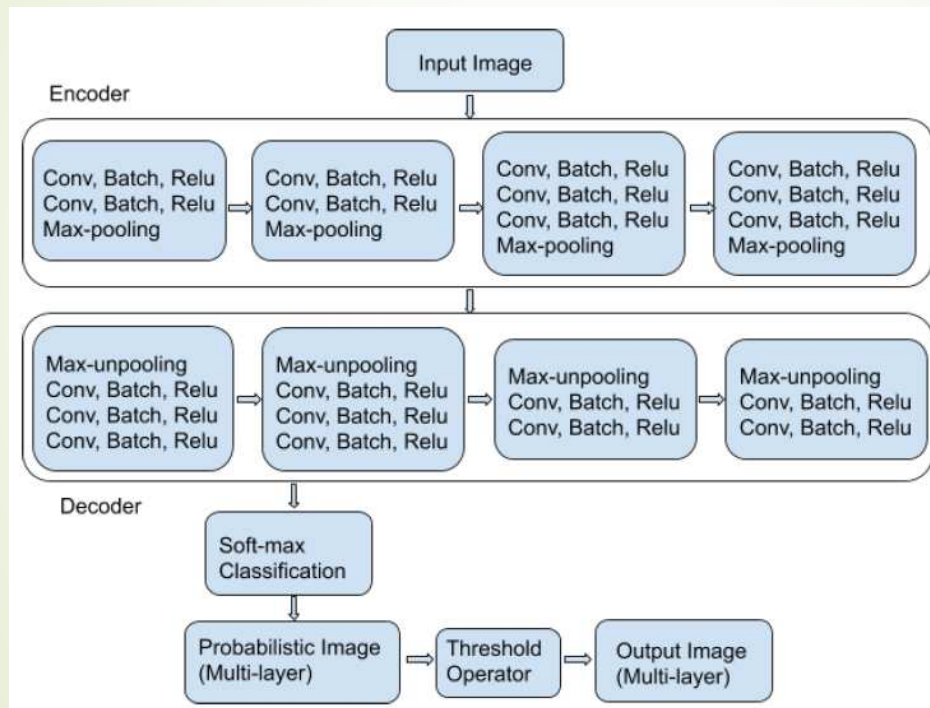


CNNs for Segmenting Translucent Partly Overlapped Objects

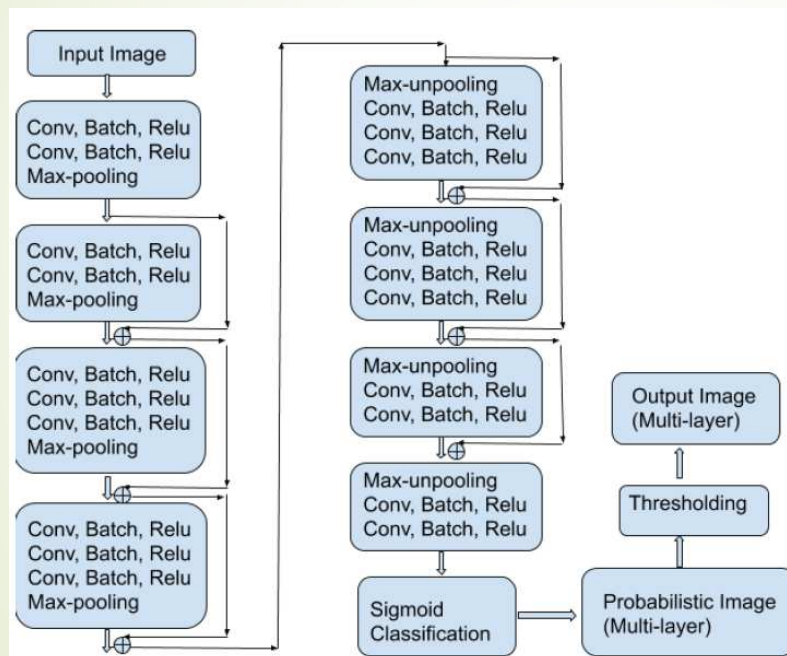
Transfer Learning



Proposed Network



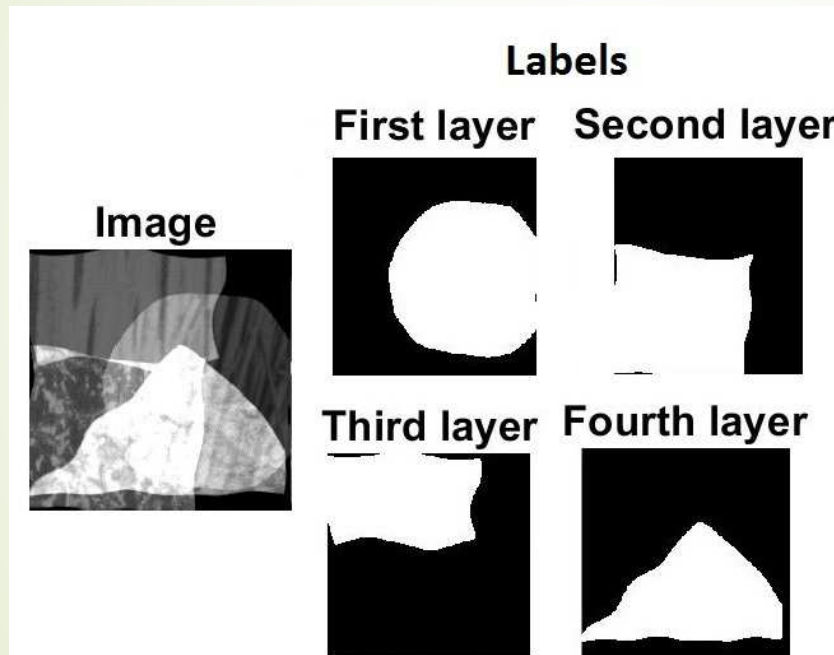
Proposed Residual Network





Results

Datasets 1



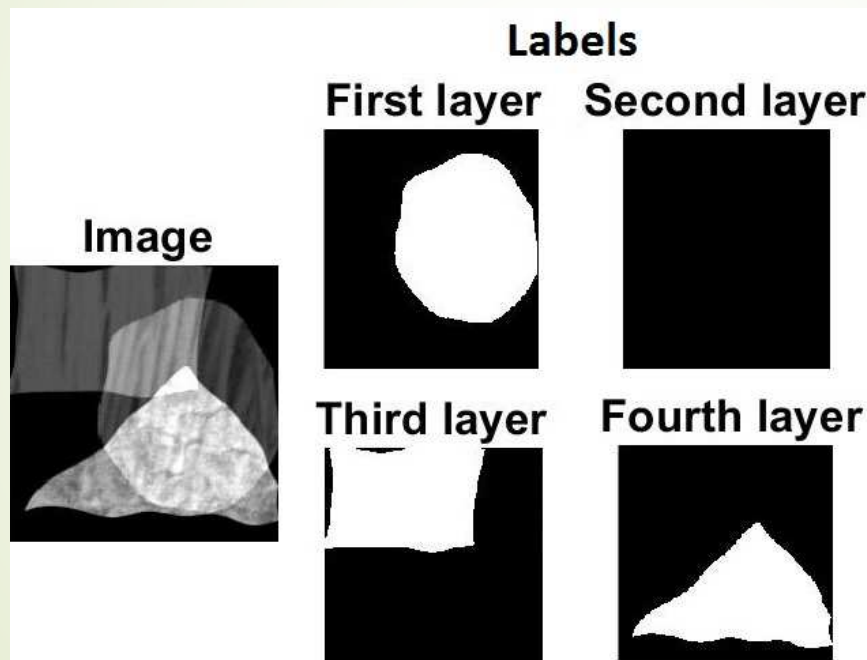
$$I = \sum_{m=1}^4 a_{m,l} * \{(O_m * P_m(x, y)) \otimes G\},$$

$$P_m(x, y) = P_m(x : x + V, y : y + W),$$

$$1 < x, \quad x + V < S, \quad 1 < y, \quad y + W < T.$$

$$a_{m,l} = a_m + N_l(0, \sigma), \quad N_l = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{l^2}{2\sigma^2}}$$

Dataset2



$$I = \sum_{m=1}^4 a_{m,l} * \{(O_m * P_m(x, y)) \otimes G\},$$

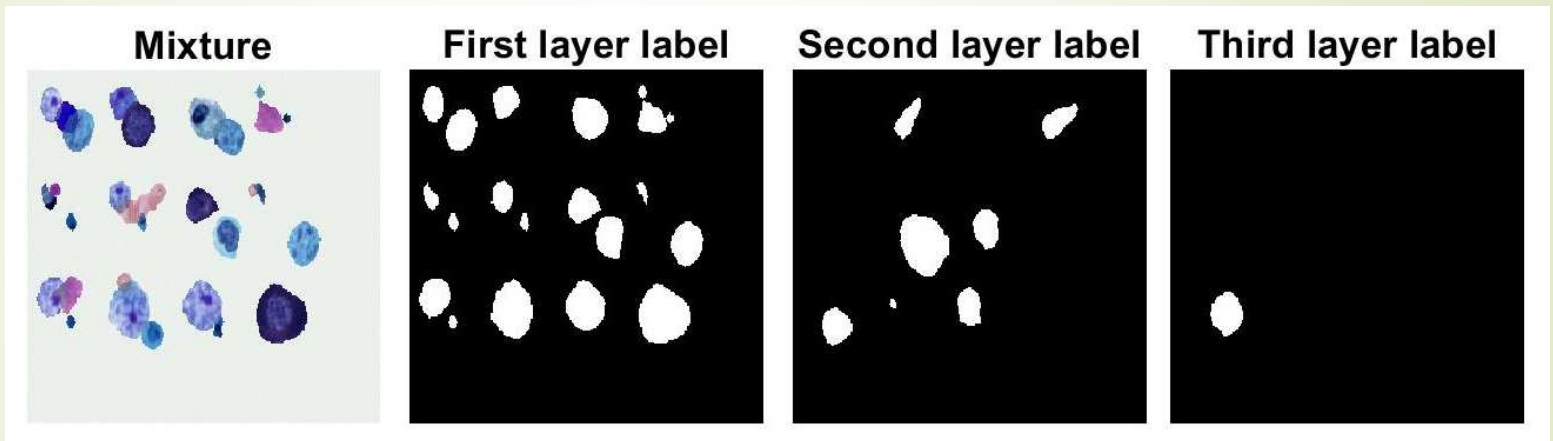
$$P_m(x, y) = P_m(x : x + V, y : y + W),$$

$$1 < x, \quad x + V < S, \quad 1 < y, \quad y + W < T.$$

$$a_{m,l} = \begin{cases} a_m + N_l(0, \sigma), & \text{if the component is selected} \\ 0, & \text{otherwise} \end{cases}$$

$$N_l = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{l^2}{2\sigma^2}}$$

Dataset3



$$F(p) = Ap + q$$

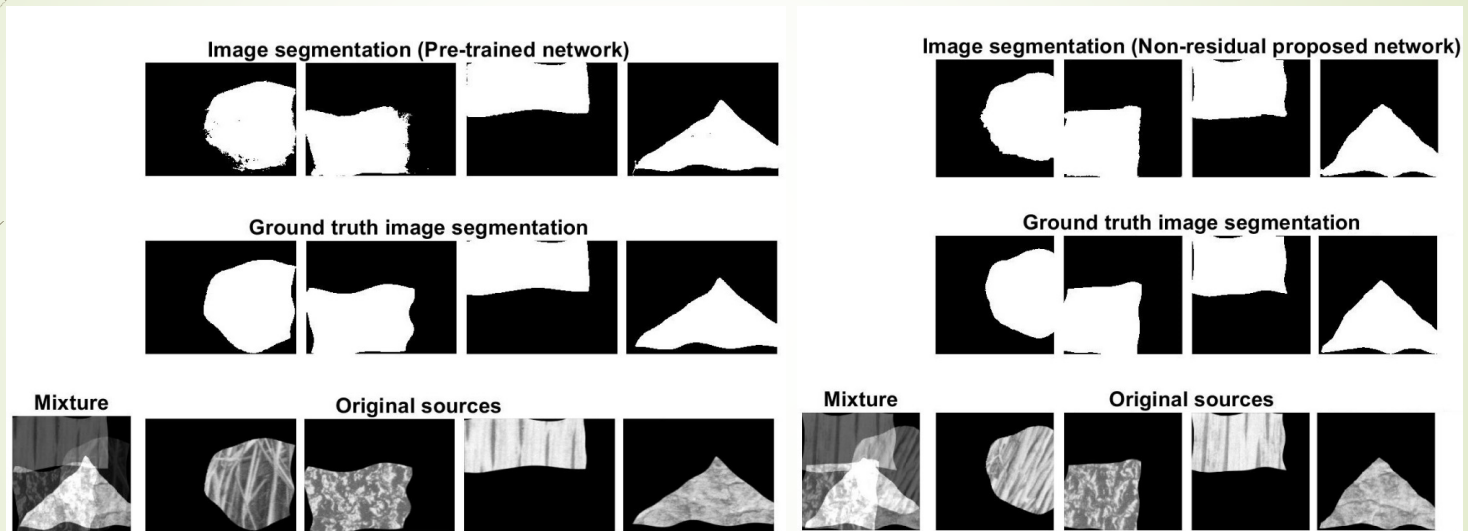
$$I_i = \sum_{n=1}^3 R_{in} + \sum_{n \neq p, n, p=1}^3 \alpha_n J_{inp} + \sum_{n=1}^3 \beta_n K_{in}$$

$$J_{inp} = \{Q_i | Q_i = O_{in} \cap O_{ip}, O_{in} \in I_{in}, O_{ip} \in I_{ip}, n \neq p, n, p = 1, 2, 3\}$$

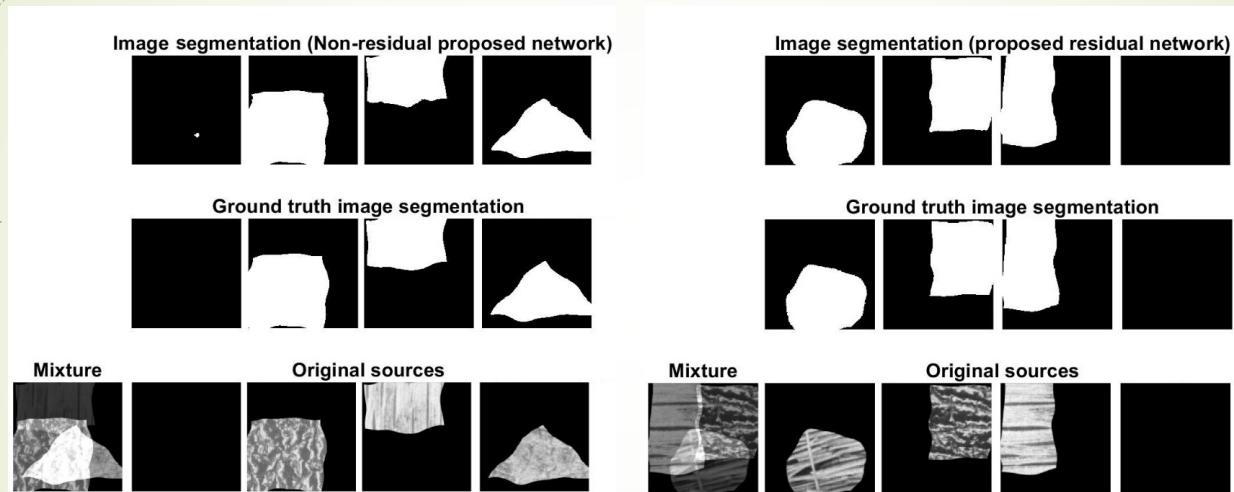
$$K_{in} = \{Q_i | Q_i = \cap_{n=1}^3 O_{in}, O_{in} \in I_{in}\}$$

$$\alpha_n = \begin{cases} 0.45 & \text{for } n = 1, \\ 0.35 & \text{for } n = 2, \\ 0.45 & \text{for } n = 3, \end{cases} \quad \beta_n = \begin{cases} 0.2 & \text{for } n = 1, \\ 0.12 & \text{for } n = 2, \\ 0.2 & \text{for } n = 3. \end{cases}$$

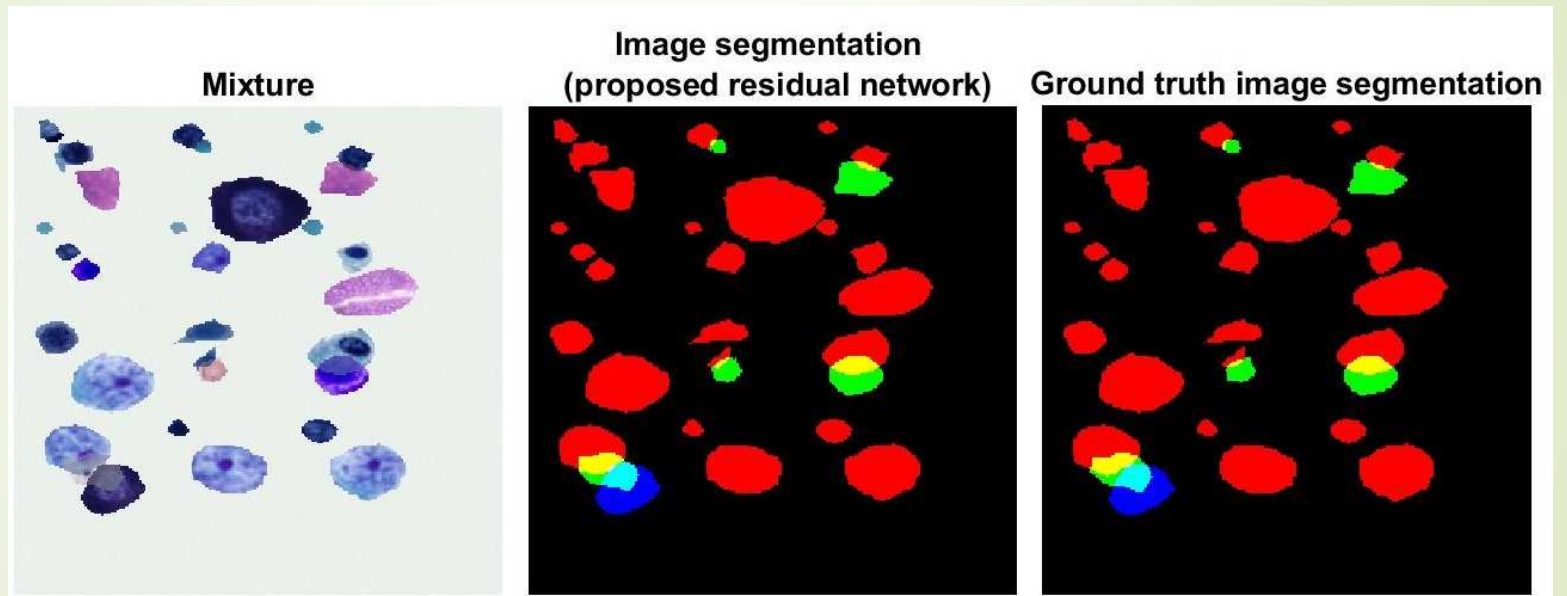
Results for Dataset 1



Results for Dataset2



Results for Dataset3



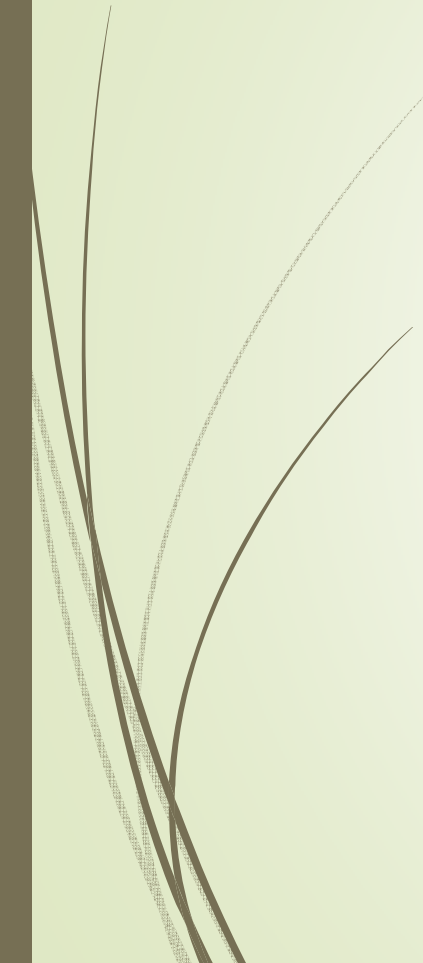
Segmentation Results

- $Acc = \frac{|\Sigma_G = \Sigma_R|}{|V|} \times 100$
- $IoU = \frac{\Sigma_G \cap \Sigma_R}{\Sigma_G \cup \Sigma_R} \times 100$

Description	Accuracy (%)	IoU (%)	Time (Sec)
Transfer_First	98.14	95.13	13425
Proposed1_First	99.06	97.48	2907
Proposed1_Second	99.37	97.59	3043
Proposed2_Second	99.55	98.07	829
Proposed2_Third	99.78	95.81	101320



Conclusion & Future Work

- CNNs for image segmentation using partially-overlapped translucent objects
 - Pre-trained network for transfer learning (SegNet)
 - New non-residual network
 - New residual network
 - Applying our residual network on real data.
- 

Questions





References



1. A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.
2. K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.
3. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. *CoRR*, abs/1409.4842, 2014.
4. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” *CoRR*, vol. abs/1512.03385, 2015.
5. V. Badrinarayanan, A. Handa, and R. Cipolla. Segnet: A deep convolutional encoder-decoder architecture for robust semantic pixel-wise labelling. *CoRR*, abs/1505.07293, 2015.
6. USC texture database. <http://sipi.usc.edu/database/database.php?volume=textures>.