Automated Segmentation of Cervical Nuclei Pap Smear Images using Deformable Multi-path Ensemble Model

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01 Motivation

- **Pap smear testing** has been widely used for detecting cervical cancers based on the morphological properties of cell nuclei in microscopic image.
- Accurate nuclei segmentation is the first step for image-based screening.
- **Image features** with **detailed structural information** and **representation capability** are vital for accurate segmentation.

02 Dataset

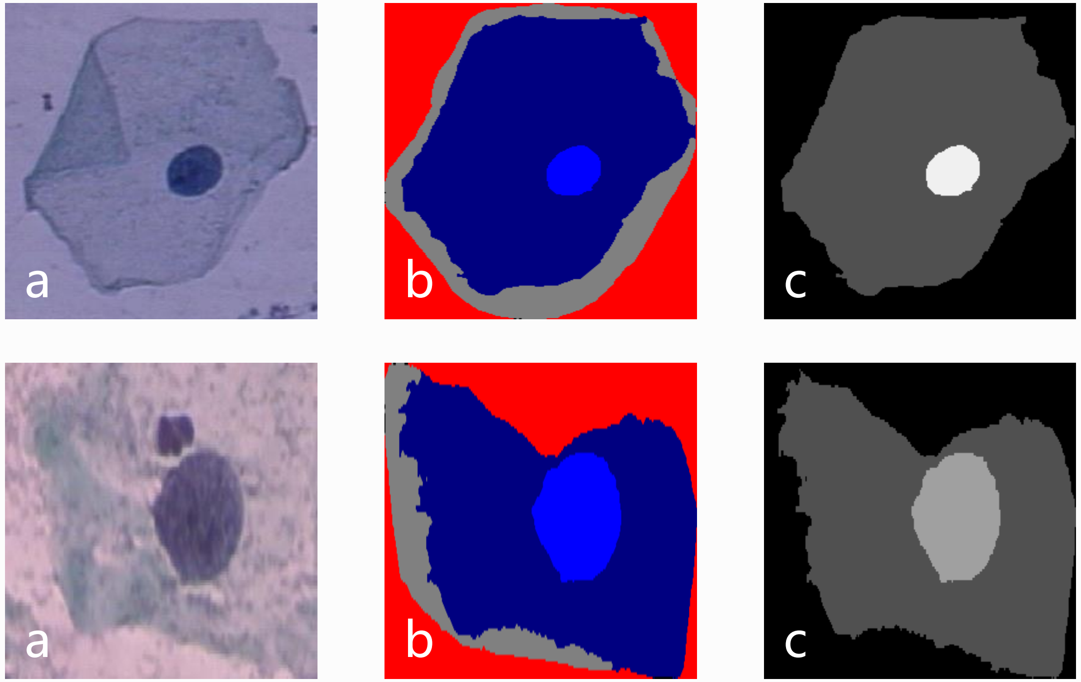


Illustration of preprocessing steps:
(a) raw Pap smear images.
(b) groundtruth with four regions.
(c) pre-processed groundtruth, bright area represents small nucleus and lightgray area represents large nucleus.

7-class:

normal columnar

normal intermediate

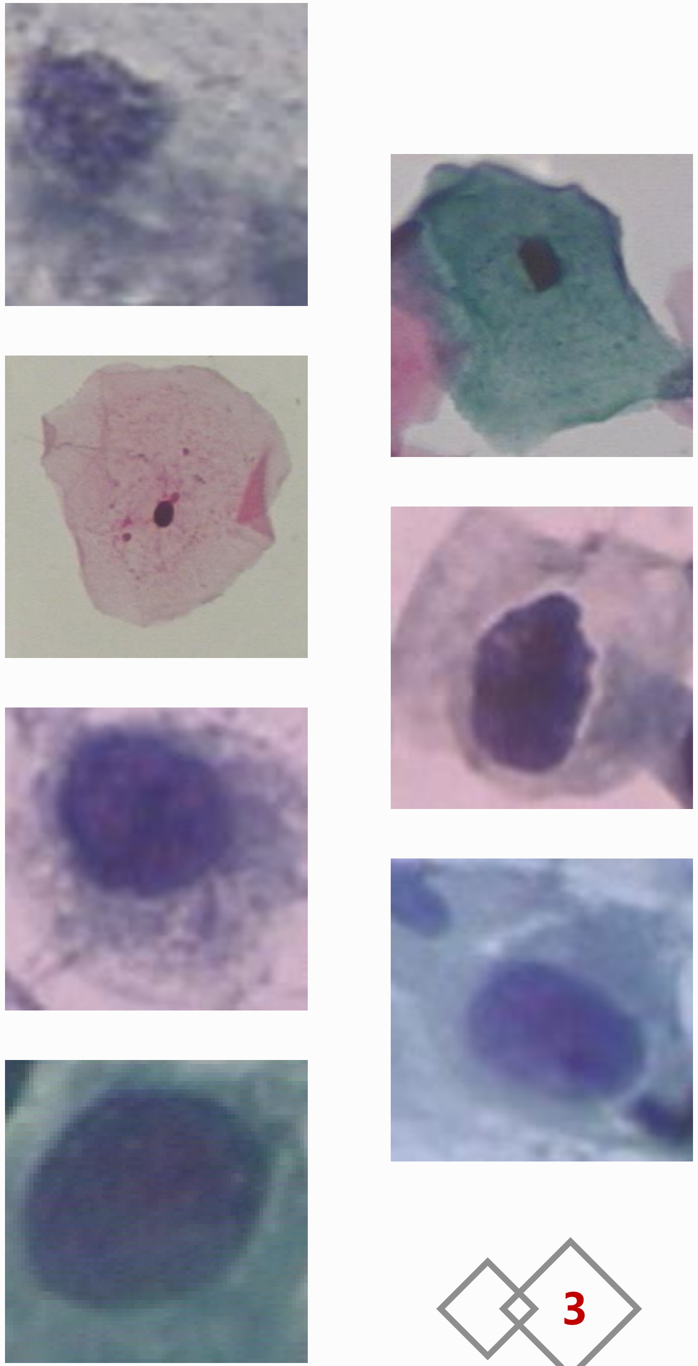
normal superficial

light dysplastic

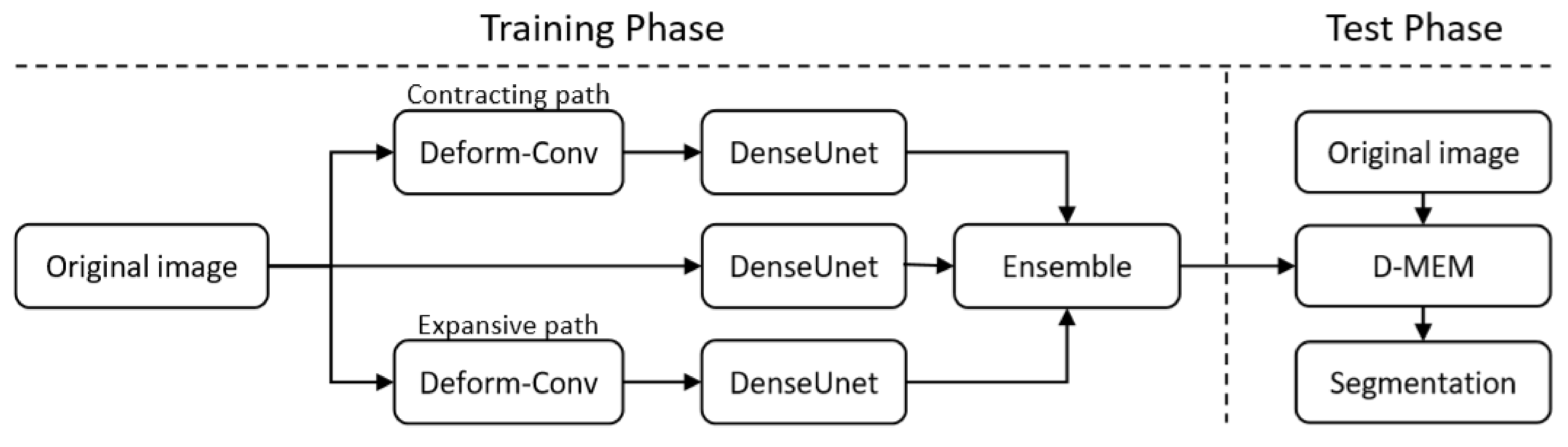
moderate dysplastic

severe dysplastic

carcinoma in situ



02 Method: Deformable Multi-path Ensemble

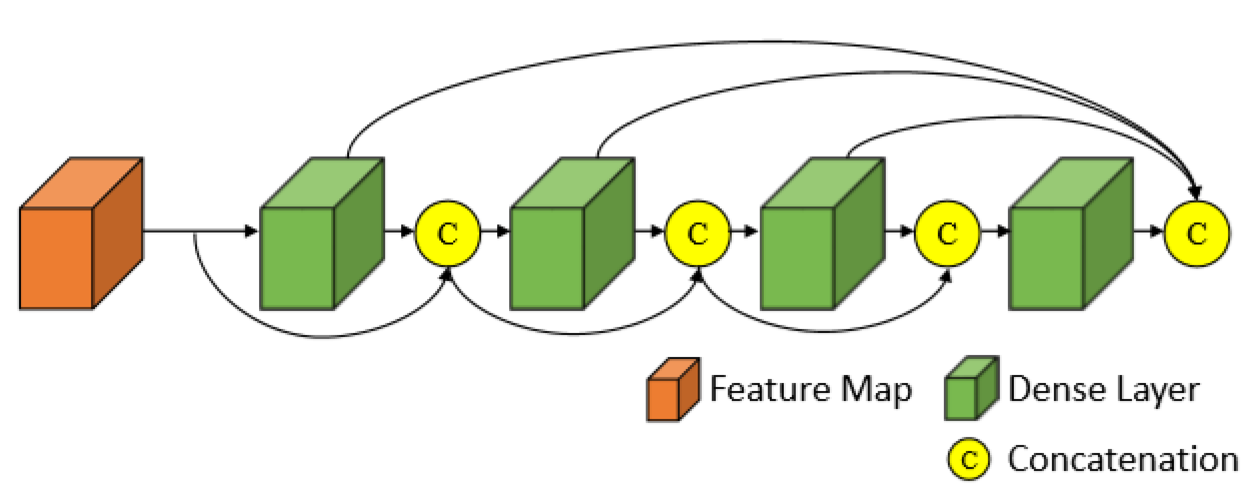


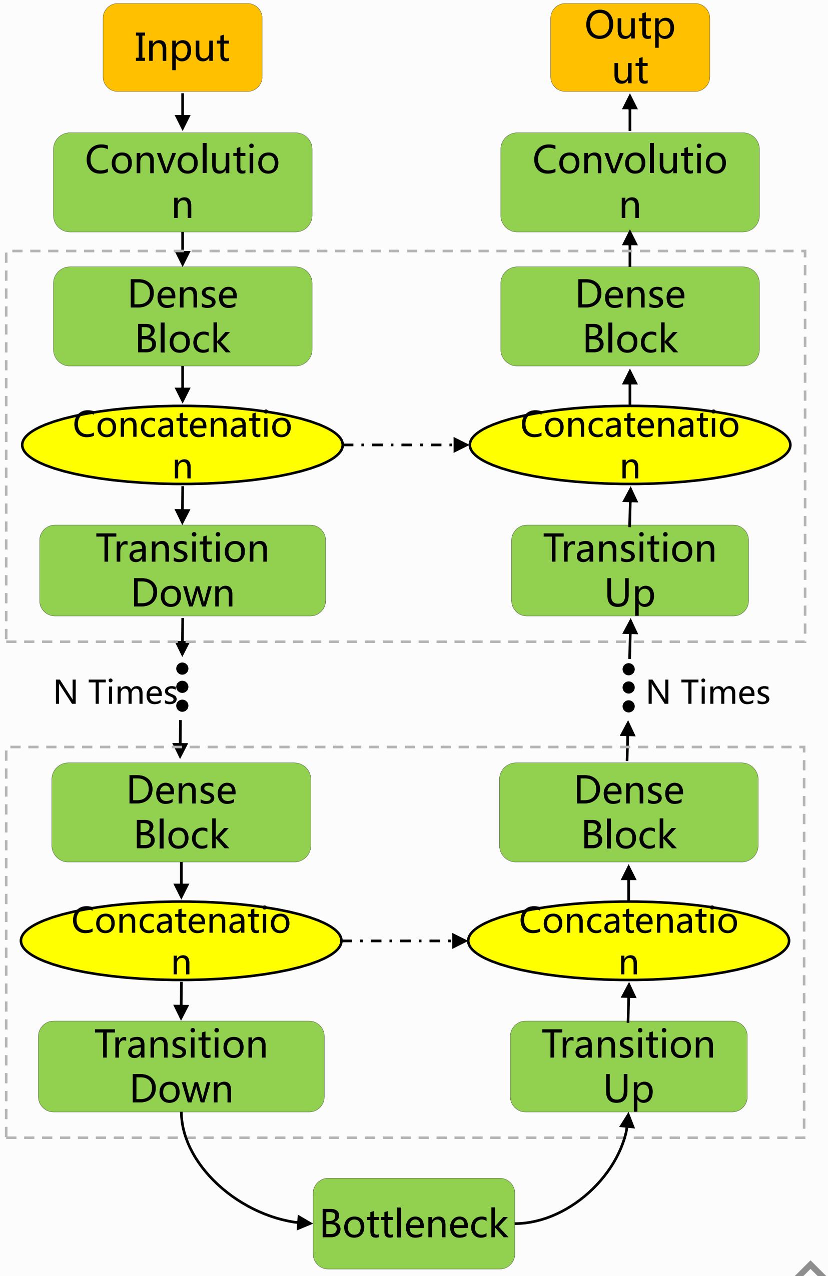
02 Method: Deformable Multi-path Ensemble

- **Dense blocks** improves information flow between neural network layers and show better capability in feature extraction.
- **Deformable convolutions** captures detailed structures of nuclei since the abnormal cervical nuclei may display irregular shape rather than circular shape of normal nuclei.
- **A multi-path fashion** trains multiple networks simultaneously with different settings and integrates the results using a majority voting strategy to further improve segmentation result.

02 Dense Block

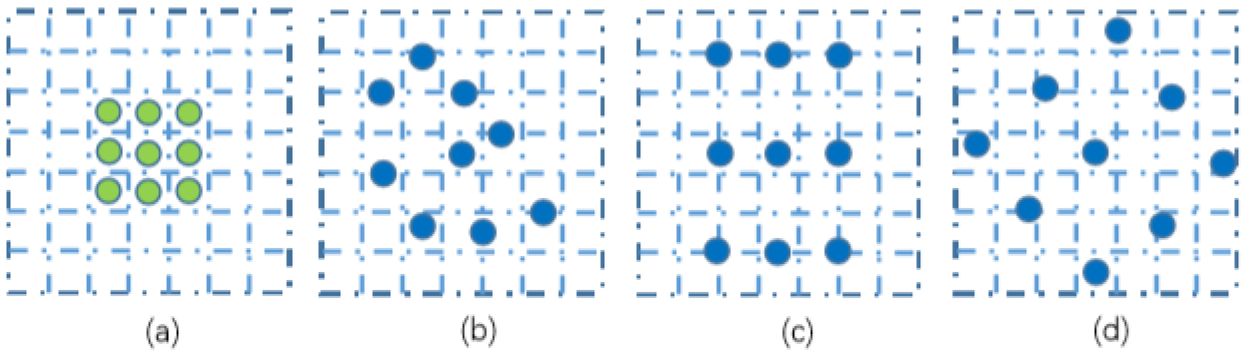
- Parameter efficiency
- Implicit deep supervision
- Feature reuse





02 Deformable Convolutional Layers

- Enhance transformation modeling capability for **adjusting receptive fields** of convolutional kernels.
- Optimizing FOV offsets for subtle structure characterization by **augmenting spatial sampling locations** on feature maps.



(a) normal convolution; (b) deformable convolution with arbitary offsets; (c-d) learned deformable convolution.

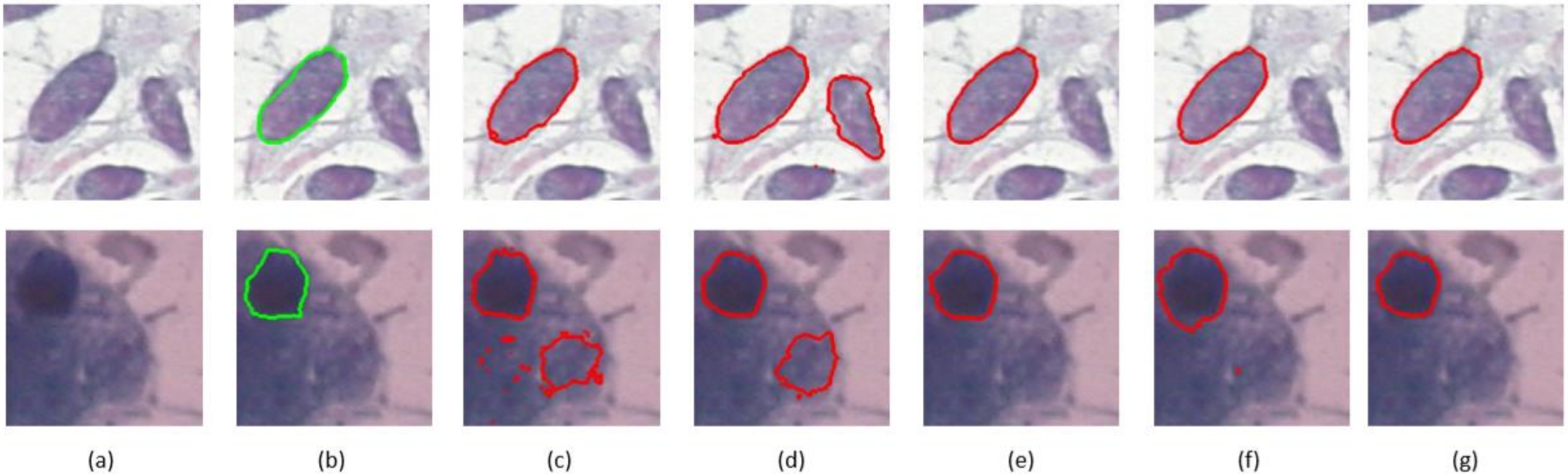
02 Multi-path Ensemble Model

- We found that: feature maps in contracting path are more related to **contextual information** and in expansive path are more related to **positional** and **morphological information**.
- Three networks are trained in a **multi-path fashion**:
  1. Dense-Unet;
  2. Dense-Unet with deformable convolutions in contracting path;
  3. Dense-Unet with deformable convolutions in expansive path;

03 Experiment and Results

- Pytorch 0.4.0 package, NVIDIA GTX 1080ti GPU with 11 GB of memory.
- Dice coefficient index as performance evaluation metric.
- All experiments are under the same set of hyper-parameters.
- Run on **Herlev dataset** consists of 917 cytological images from Pap smear tests.
- All images are **normalized** to have zero mean with unit variance intensity and are resized to size of 256×256.

03 Experiment and Results



Examples of segmentation results. (a) Pap smear images, (b) Manual annotations, (c) Segmentation results of Unet, (d) Segmentation results of dense U-Net, (e) Segmentation results of D-Con (deformable convolutions in contracting path), (f) Segmentation results of D-Exp (deformable convolutions in expansive path; (g) Segmentation results of D-MEM (multi-path ensemble).

03 Experiment and Results

Method	ZSI	Precision	Recall
Unsupervised[15]	0.89±0.15	0.88±0.15	0.93±0.15
FCM[16]	0.80±0.24	0.85±0.21	0.83±0.25
P-MRF[17]	0.93±0.03	–	–
SP-CNN[18]	0.90	0.89	0.91
Our Method	**0.933**±0.14	**0.946**±0.06	**0.984**±0.00

Quantitative comparison of state-of-the-art methods with our proposed method in terms of mean(± standard deviation) of ZSI, precision and recall rates.

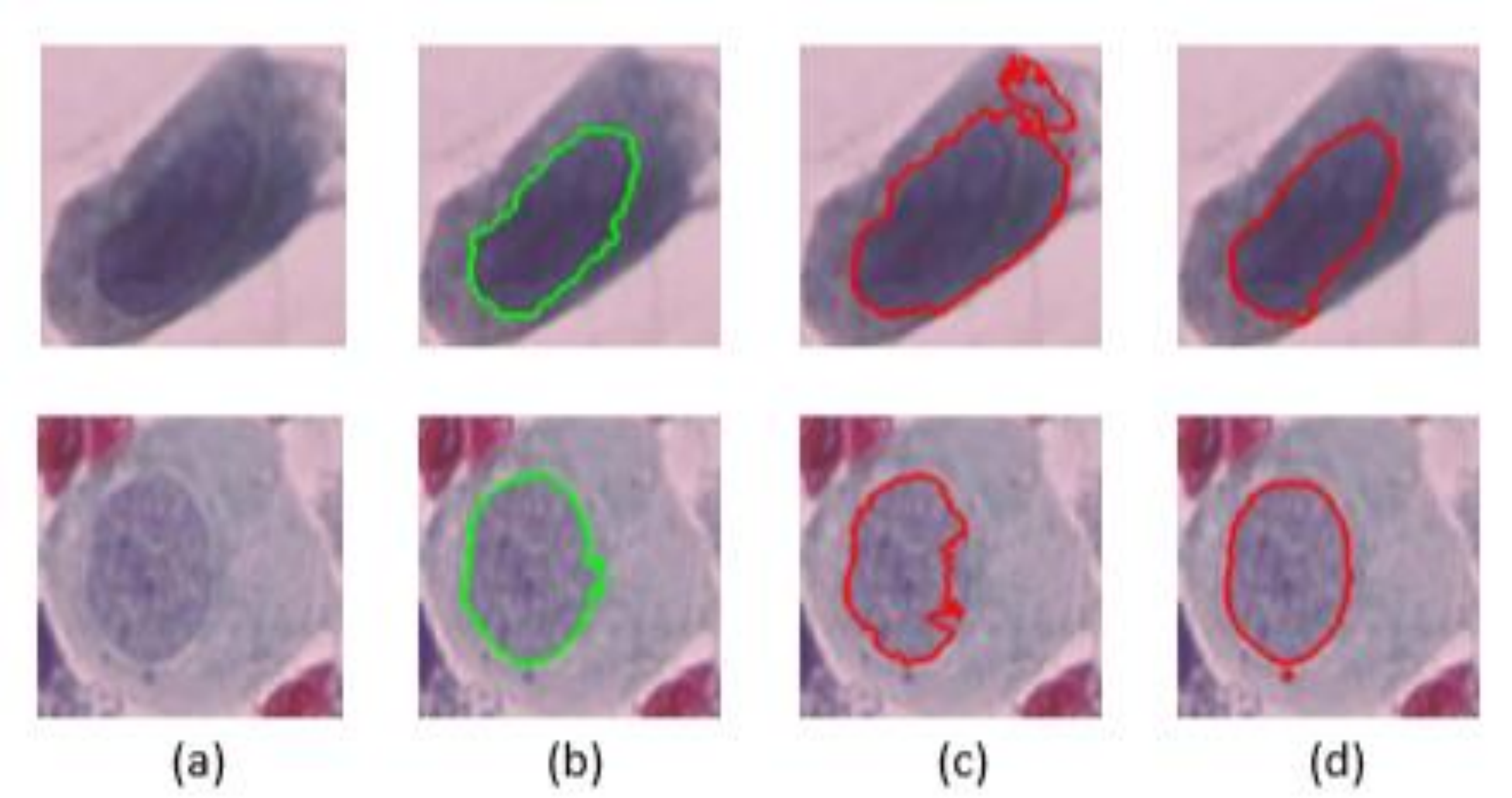
[15] Aslı Genc¸Tav, Selim Aksoy, and Sevgen O¨ Nder, "Unsupervised segmentation and classification of cervical cell images," Pattern recognition, vol. 45, no. 12, pp. 4151– 4168, 2012.
[16] Thanatip Chankong, Nipon Theera-Umpon, and Sansanee Auephanwiriyakul, "Automatic cervical cell segmentationand classification in pap smears," Computermethods and programs in biomedicine, vol. 113, no. 2,pp. 539–556, 2014.
[17] Lili Zhao, Kuan Li, Mao Wang, Jianping Yin, En Zhu,Chengkun Wu, Siqi Wang, and Chengzhang Zhu, "Automaticcytoplasm and nuclei segmentation for colorcervical smear image using an efficient gap-search mrf," Computers in biology and medicine, vol. 71, pp. 46–56,2016.
[18] Srishti Gautam, Arnav Bhavsar, Anil K Sao, and KK Harinarayan, "Cnn based segmentation of nucleiin pap-smear images with selective pre-processing," in Medical Imaging 2018: Digital Pathology. International Society for Optics and Photonics, 2018, vol. 10581, p.105810X.

Experiment and Results

Methods	U-Net	Dense-Unet	D-Con	D-Exp	**D-MEM**
ZSI	0.869	0.910	0.918	0.917	**0.933**
Precision	0.897	0.893	0.888	0.894	**0.946**
Recall	0.879	0.956	0.972	0.961	**0.984**

Comparison among different model settings.

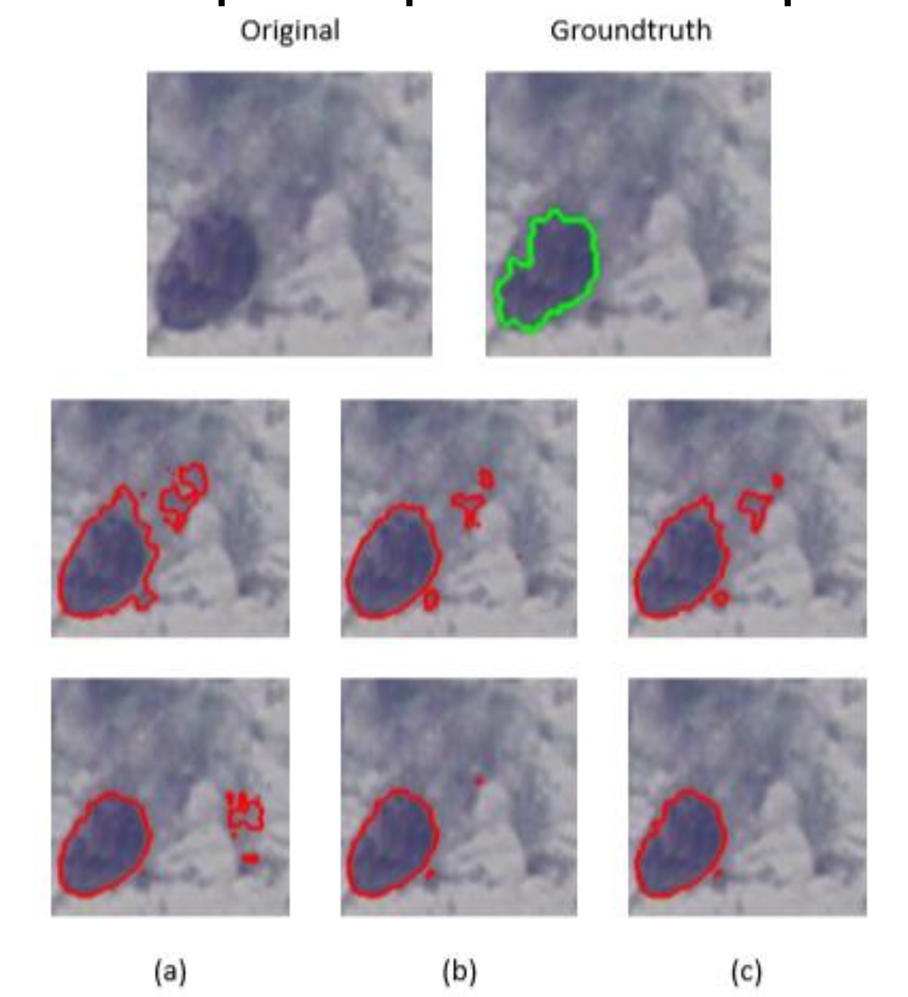
Effect of dense connection: Experiment on Herlev dataset shows that performance of Dense-Unet (0.910) is better than U-Net (0.896).



(a) Input images. (b) Ground truth. (c) Segmentation results of U-Net. (d) Result of Dense-Unet.

04 Discussion

Effect of deformable convolution: deformable convolution layer is providing extra spatial prior and improves the results.



(a)Dense U-Net.

(b)D-Con.

(c)D-Exp.

04 Discussion

Effect of number of parameter (i.e. network size): the more parameters are used, the better segmentation performance is. If the number of parameters is increased Further, we could extend the ensemble model to more varieties (currently ensemble 3 models) to further improve segmentation performance.

Thank You!