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PREDICTING THE LOCATION OF THE UTERINE CERVICAL OS FROM 2D IMAGES WITH CNN

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Cervical os Prediction,
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Convolutional Neural Networks,
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Abstract

In an automated cervical cancer test, the prediction of the location of the cervical os from 2D images is required. Cervical os is the reference point to determine the lesion's location by either using cervical four-quadrant location or by 12 o'clock locations. Precise detection of the cervical os point ensures correct addressing of the lesions. This study used a 6-layer convolutional neural network to predict the center of the cervical os' coordinates (x,y) on 2D grayscale images. We used a holistic approach without masking any visual element to predict the location of the cervical os. The 2D images were obtained using a telecentric lens and a CCD camera with light wavelengths of 500-550 nanometers. Due to a limited number of training samples (145 images), we used augmentation techniques to increase the training set size by rotating each original image in 1-degree increments from -30 degrees to +30 degrees relative to the center of the image. The 6-layer convolutional neural network was tested on 21 unseen cervix images using augmentation data. The outcomes showed that the image center-based augmentation technique improves the prediction performance. We obtained 2.4 RMSE in predicting the location of the cervical os.

CNN İLE 2B GÖRÜNTÜLERDEN SERVİKAL OS KONUMUNU TAHMİN ETME

Anahtar Kelimeler
Servikal Os Tahmini,
Serviks Uteri,
Evrişimli Sinir Ağları,
Veri Çoğaltma

Öz

Otomatik bir rahim ağzı kanseri testinde, 2 boyutlu görüntülerden rahim ağzının yerinin tahmin edilmesi gerekir. Servikal os, dört kadran konumu gösteriminde veya 12 saatlik dilimler halindeki gösterimde her bir konumun yerini belirlemek için referans noktası olarak kullanılmaktadır. Servikal os noktasının hassas tespiti lezyonların doğru adreslenmesini sağlar. Bu çalışmada, 2 boyutlu gri tonlamalı görüntülerde servikal os koordinatının (x, y) merkezini tahmin etmek için 6 katmanlı bir evrişimli sinir ağı kullanılmıştır. Servikal os' un yerini tahmin etmek için herhangi bir görsel unsuru maskelemeden bütünsel bir yaklaşım kullandık. Çalışmada kullanılan iki boyutlu görüntüler, bir telesentrik lens ve 500-550 nanometre ışık dalga boylarına sahip bir CCD kamera kullanılarak elde edildi. Sınırlı sayıda eğitim örneği (145 görüntü) nedeniyle veri, büyütme tekniklerinden faydalanılarak her bir orijinal görüntü, görüntünün merkez noktasına göre -30 dereceden +30 dereceye kadar 1 derecelik artan açılar ile döndürüldü. Bu veriler üzerinden öğrenme yapan 6 katmanlı evrişimli sinir ağı, daha önce görülmeyen 21 serviks görüntüsü üzerinde test edildi. Sonuçlar, kullanılan görüntü merkezi tabanlı büyütme tekniğinin tahmin performansını iyileştirdiğini gösterdi. Servikal os lokasyonunun tahmininde 2.4 RMSE değeri elde edildi.

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1. Introduction

According to WHO 2018 data, cervical cancer is the fourth most common cancer among women worldwide. Therefore, cervical screening has great importance for women's health. The cervix is part of the female reproductive system located in the lower part of the uterus in the pelvis. Either PAP smear or colposcopy tests can do cervix screening. Visual inspection of Acetic Acid is another alternative for cervical screening. In visual inspection, the cervical surface is addressed by either four quadrants or 12 o'clock surface locations as shown in Figure 1.

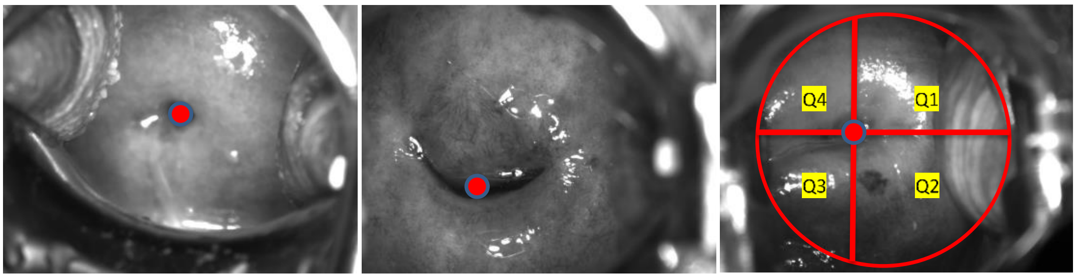

Figure 1. The Red Points Represent the Center of the Cervical Os in Different Cervix Uteri Images. The Four Quadrants Formed on the Surface of the Cervix (Red Circle) Relative to the Cervical Os.

In both quadrant and o'clock based methods, the origin is the cervical os (simply the os). Therefore, the detection of the location of cervical os is the first step in these methods. Detection of the cervical os is a straightforward process for expert people, but it is hard for computers due to varying factors on the cervical surface such as different visuals (e.g. vaginal speculum), specular reflections due to fluids, aging, number of previous births, etc. Figure 2 shows varying examples of cervix uteri images.

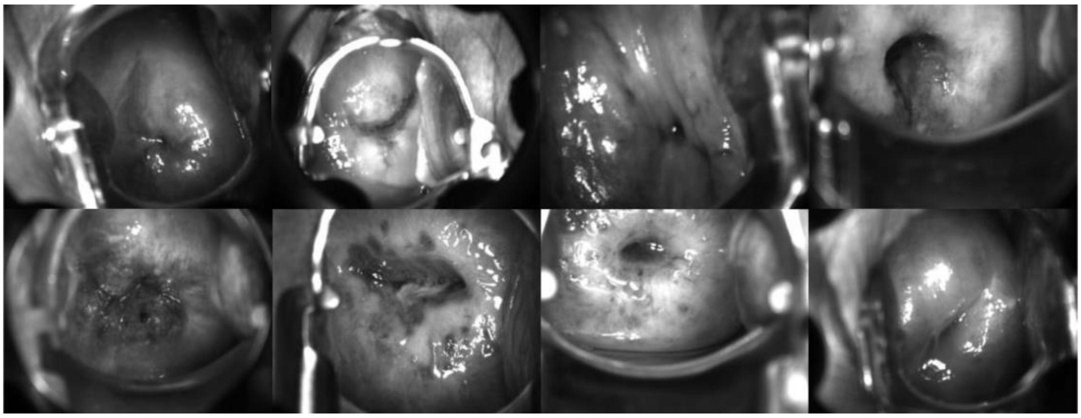

Figure 2. Visual Variations in Cervix Uteri Images.

In this study, we proposed a deep convolutional network for cervical os detection in 2D grayscale images. Our study has shown that the use of holistic approach combined with augmentation techniques provide accurate cervical os predictions. The main contribution of the study is two-fold: First, our method does not require extensive preprocessing operations for cervical os prediction. Second, our experiments showed that the use of augmentation techniques improves the overall precision of the prediction.

We present the literature survey in Section 2. Material and method is provided in Section 3. Section 4 presents the experimental results on cervical os prediction. Finally, Section 5 gives a summary and conclusion of the study.

2. Literature Survey

Segmentation of medical images has been actively studied in the literature (Xue et al., 2007; Kudva et al., 2017; Liu et al., 2018; Guo et al., 2020) to segment the cervical surface, the cervical os, and the transformation zone. In these methods cervical os can be defined as a single point showing the center of mass of the segmented region. On the other hand, these methods can be affected by the specular reflections. To improve the segmentation's quality, specular reflection detection, and elimination are generally employed (Lange, 2005; Das et al., 2011; Patil et al., 2016; Kudva et al., 2017).

Cervical os is a gate for the cervical canal, so it is defined either by a region or by a point. (Greenspan et al., 2009) proposed a framework for anatomical landmark detection in uterine cervix images for automated cervigram analysis. They first defined a coarse region of interest (ROI) to eliminate outliers such as vaginal walls. Using CIE-Lab color space, they clustered the image pixels concerning the image center, assuming that the center the image center is close to the cervical os. The center of the image found a relatively pink color that corresponds to the cervix region. After that, the os is detected by measuring local concavity features on the intensity gradient image. Extending the convexity operator towards the positive x-axis results in a strong reaction to the os location. They measure the performance of the os detection by the distance to the ground-truth in terms of pixels. According to their experiments, 87% of the case, the distance between the predicted location and ground-truth location is less than 10 pixels at 1500×2500 resolution. Similarly, 76% of the cases, the difference is less than 5 pixels. Unfortunately, the image resolution is not reported. This method assumes that the os is horizontally oriented and it is based on handcrafted features. Therefore, if there is no visible orientation, the localization is not possible in this approach.

As opposed to the previous studies, we used a holistic approach in combination with convolutional neural networks (CNNs) without eliminating the specular reflections to determine the location of the os. CNNs are known for their success in classifying, segmenting and predicting image-driven problems. Therefore, we kept the surrounding visuals such as vaginal folds and vaginal speculum to cover variety of cervix images.

3. Material and Method

We modeled the prediction of cervical os regression using convolutional neural network architecture. Convolutional neural networks need many training samples for accurate predictions. For this reason, we used pipelined augmentation techniques to increase the number of samples.

3.1. Data Augmentation

Our dataset consists of 181 cervix uteri images obtained from 54 individuals. The original images are in grayscale and having a resolution of 1912×1452. A medical expert manually marked each image for the cervical os. We randomly select 80% of the training images for the train, and the remaining 20% is equally divided into validation and test set. In our dataset, each subject has 3-4 cervix samples. To prevent data leakage, we split the dataset by considering identities. As a result, our train, validation and test set consist of 145, 18 and 18 images.

Image rotation, translation, and scale are factors enriching the input data. Since we have a limited number of training samples (145 images), we used augmentation techniques to increase the training set size. To do that we rotated each original image in 1-degree increments from -30° to 30° relative to the center of the image. To do that first we performed rotations and then cropping of input images. This process provides 8,845 images from 145 original images. After each rotation, we randomly generate a 2D point (x', y') in the range from 0 to 10 pixels at 63×48 resolution to simulate a variety of camera to cervix distances. It allows us to cover possible shifts in horizontal and vertical axes. However, cervical os may disappear due to image center-based rotation in some images. In our tests, we ignored such cases. Figure 3 shows augmented samples excluding the original image obtained from a single cervix uteri image.

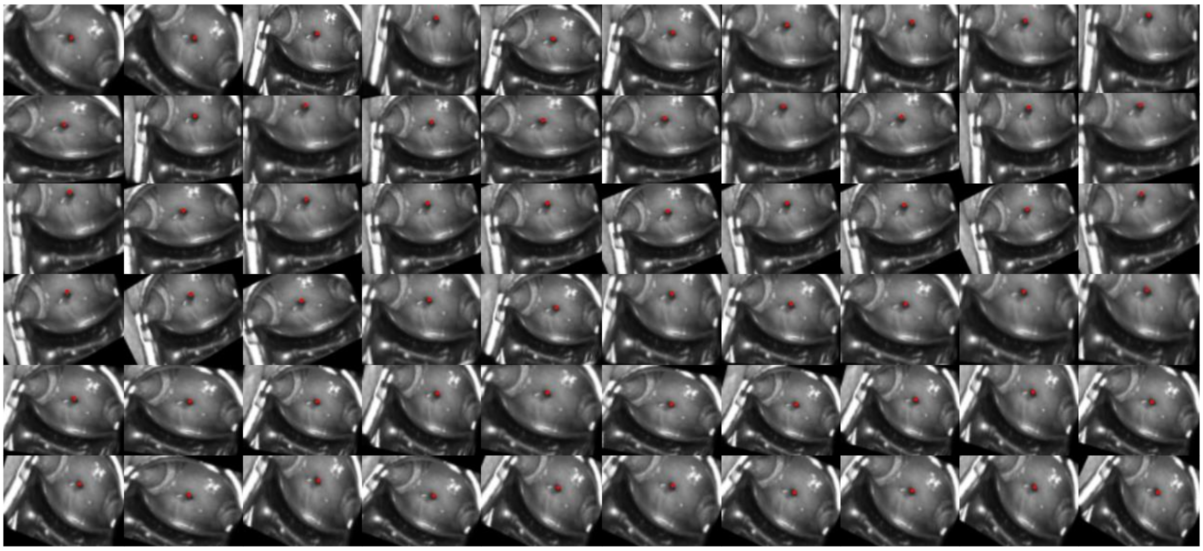

Figure 3. Augmented Samples and Cervix Os (Red Dot).

3.2. Proposed Method

Our convolutional neural network consists of four convolutional layers with ReLU activations, Max pooling and finalizes with the two fully connected layers to predict (x ,y) location of the cervical os as shown in Figure 4 We defined the batch size as 16, and validation size as 10% of the training data. The original image size was reduced by 30% from 1912×1452 to 63×48 for efficient processing. Adam is used as the optimizer with a scheduled learning rate of 0.001 at the beginning.

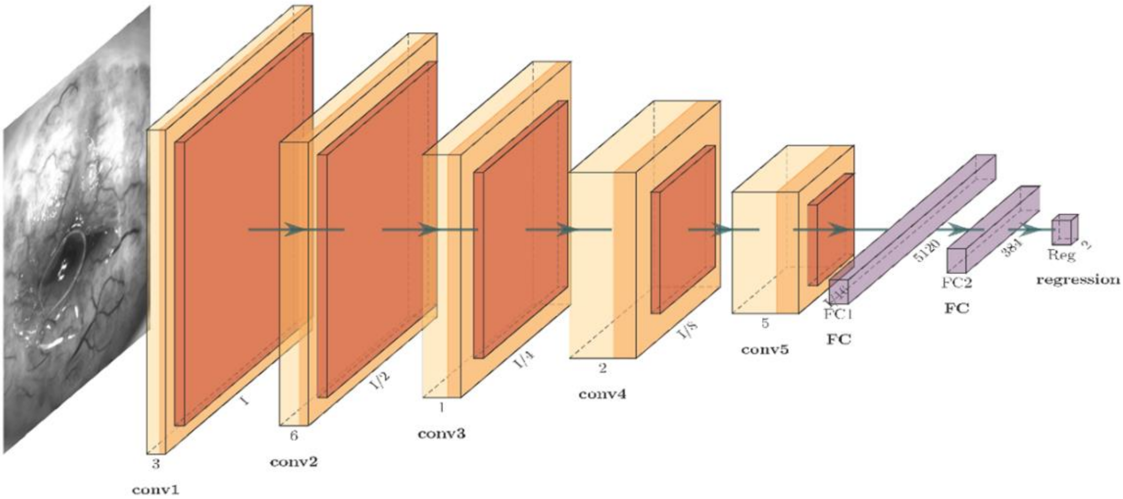

Figure 4. Our 6-Layer Convolutional Neural Network Architecture to Predict the Cervical Os.

The training process lasts 100 epochs and the learning rate is halved after every 20 epochs. We applied dropout regularization of 0.2 for reducing overfitting and improving the generalization ability on each of the fully connected layers. Besides that, we randomly change the aspect ratio of the input images up to 10 pixels in each axis to reduce overfitting in each epoch.

3.2. Evaluation

To evaluate the performance of the proposed method, we used RMSE where d_i is the square of the distance of the point predicted by the model to the ground-truth position. If the ground-truth location $p_i = (x_i, y_i)$ and predicted location $q_i = (x'_i, y'_i)$, then the distance and RMSE is given by Equation (2) using Equation (1) where N is the number of test images.

$$d_i = \mathrm{d}(p_i, q_i) = (x_i - x'_i)^2 + (y_i - y'_i)^2 \qquad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{\text{N}}\sum_{i=1}^{N} d_i} \qquad (2)$$

4. Experimental Results

We conducted our experiments on the cervix images obtained from different persons using the same camera configuration. Pytorch is used for the implementation. A single epoch on the CPU (Intel i7 7700 3.6 GHz) requires 15.8 seconds for 8,845 image of resolution 63×48. The same epoch took 3.8 seconds on a GPU (Nvidia GTX 1060 6GB).

The cervical os is represented by an (x, y) tuple where x and y show the cervical os position scaled in the range [0,1] by normalizing the width and height of the image, respectively. We trained our network on 63×48 resolution. Figure 5 shows the loss values and the change of the learning rate during training. In the application, we used the trained model having the lowest validation loss instead of the last model generated in the last training epoch and obtained RMSE of 2.4 on the unseen test samples.

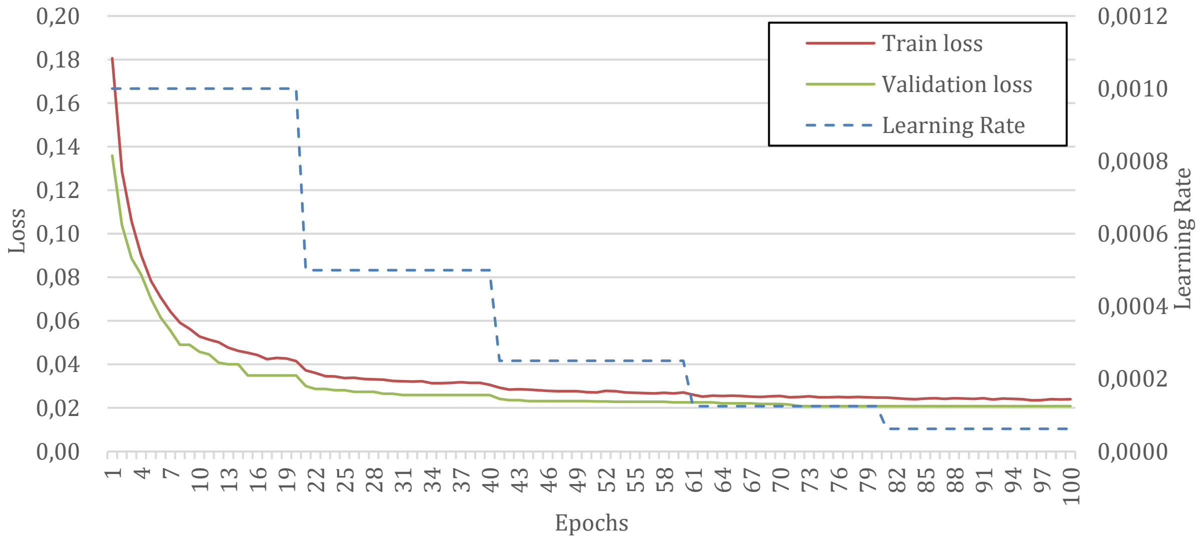

Figure 5. Training and Validation Loss During 100 Epochs.

Figure 6 shows example images having the lowest and highest errors using Equation (2) at 63×48 resolution.

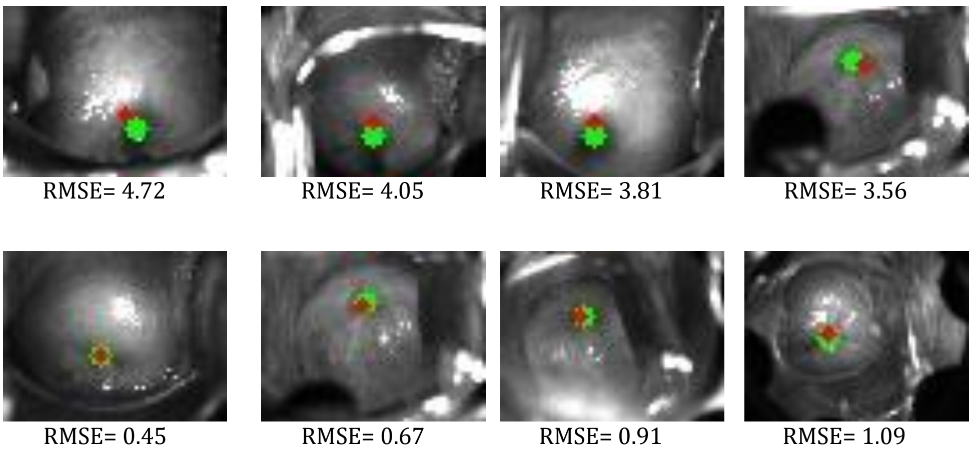

Figure 6. Examples from Cervical Os Prediction Results Where the Green Point Represents the Ground-Truth and the Red Point Represents the Predicted Location for the Center of the Cervical Os. The First Row Shows the Test Images Having the Highest RMSE and The Second Row Shows the Test Images Having the Lowest RMSE.

According to the visual inspection on the prediction results, RMSE increases with the increasing visuals of cervix images having vaginal walls, and vaginal speculum. Similarly, it decreases when the image contains mostly the cervical region with less background elements. In order to support the visual inspection results, we performed gradual cropping of the input images to focus more on the cervix region without changing the 63×48 resolution by using linear interpolation. Our experiments showed that precise detection of the cervical os is possible with a basic CNN architecture using augmentation techniques. We obtained RMSE of 2.4 at 63×48 resolution.

5. Result and Discussion

In cervical screening, the location of the lesions is determined relative to the cervical os. We developed a CNN to predict the location of the cervical os using 2D cervix uteri images. We used a holistic approach to detect cervical os. Therefore, we did not segment or exclude any part of the cervix image. We improved the prediction accuracy by using augmented data and obtained RMSE of 2.4. Since the RMSE value is computed from pixel-based distance, the input resolution has direct effect on the RMSE value. Therefore, we believed that it must also be normalized with respect to the cervix radius. As a future work we are planning to normalize the RMSE value and perform test time augmentation and ensemble techniques to decrease the variance and improve the precision for cervical os detection.

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Conflict of Interest

No conflict of interest was declared by the authors.

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