

Cervical Cancer Image Classification Using CNN Transfer Learning

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ABSTRACT

Cervical cancer is a major global public health problem, Indonesia is among top 3 countries in the world with the highest number of cervical cancer incidents. An early diagnosis for cervical cancer is one of the key approaches to prolong patient's life expectancy. The Papanicolaou (Pap smear) test is a cervical cancer screening test that has been widely utilized. Pap smear test is a tedious, labour-intensive, and time-consuming task, which leads to high inter operator's variability. A computer-based classification algorithm to assist the task has been proposed. In this paper we focus on the approaches using Convolutional Neural Network (CNN) to handle the classification task. Moreover, our proposal employs a parameter efficient model. Thus, the computational cost is greatly reduced. We use a transfer learning method for model adaptation. We trained the pre-trained SqueezeNet architecture with the three class of pap smear images dataset in caffe. The fine-tuning process was started with the initialization of the model's features to the object's broader spectrum. Then, the last layer output number was changed to fit the number of labels for cervical cancer class.

Keywords: Cervical Cancer, Image Classification, CNN, Deep Learning.

1. INTRODUCTION

Cervical cancer is a major global public health problem, especially in less-developed countries. China, India, and Indonesia are the top 3 countries with the highest number of cervical cancer incidents (all ages) [1]. Cervical cancer is a preventable and curable disease caused by human papillomavirus (HPV) [2]. Yet it is the second world highest cancer incidents (23.4 per 100,000) and mortality (13.9 per 100,000) rates [3]. Vaccination is an effective method to prevent cervical cancer [4]. Still, it is affordable in only 46 countries with high per capita Gross Domestic Product (GDP) [5]. Thus, the development of an effective early detection method is critical. The treatment at the early stage of cervical cancer is cost-effective [6]. Also, early diagnosis help increases the patient's probability of cure and treatment which increases the patient's life expectancy.

The Papanicolaou (Pap smear) test is a cervical cancer screening test that has been widely utilized [7]. It is reported to be successful in reducing 50%-70% cervical cancer mortality rate in developing countries due to its high specificity (0.98) [5], [8]. In the pap smear test, the sample is collected from the cervical 'transformation zone' using a cervical brush. Subsequently, the sample

spread onto a glass slide, stained, and preserved. The prepared sample's glass slides then observed under a microscope [7]. An average pap smear slide contains 50,000-300,000 cells that must be manually examined [7]. Hence, it is a tedious, labour-intensive, and time-consuming task, which leads to high human error probability. McCrory, et al [9] reported that the sensitivity of the pap smear test is low i.e., 0.51. High false-negative result (20-30%) of the Pap smear test also reported due to the difficulty in observing clumping cells [7]. Therefore, the development of technologies for rapid, cost-effective, and sensitive cervical screening methods is necessary.

Automated screening system of pap smear images has become a promising alternative due to their rapidity, accuracy, reliability [10]. Sharma, et al [11] introduced the K-Nearest Neighbour (KNN)-based classification of cervical cancer clinical dataset. The pap smear images first segmented by Edge Detection to collect the cell nuclei. Then the features i.e., area, perimeter, and elongation are extracted and later normalized by the min-max method. Afterward, the classification was done with the KNN method. However, the model achieved relatively low accuracy. William, et al [10] reported that from most of the introduced machine-learning-based

cervical cancer diagnosis and classification, there is some undeniable weakness that results in low cell classification accuracy. Deep learning based models have made an impressive advance in various medical imaging [12] – [15]. In cervical cancer, Xiang, et al [16] developed Convolutional Neural Networks (CNN)-based on deep learning method for cervical cancer reading with YOLOv3 as the baseline model. An additional task-specific classifier was added to improve the classification performance. The presence of unreliable annotation was handled by smoothing the noisy label’s distribution. The evaluation showed that the model has high sensitivity, but the specificity is still insignificant. Hussain, et al [17] reported various model based on deep convolutional neural networks i.e., Alexnet, VGGnet, Resnet, and GoogleNet architectures for cervical cancer diagnosis. The fine-tuned models proven to have high accuracy. However, the utilization of these architecture are time consuming and need a large memory computation [18].

To cope with this problem, in this work we adopt CNN based SqueezeNet architecture for early detection of cervical cancer from pap smear images. Compared to other architecture, SqueezeNet has some main advantages i.e. (1) The network is more efficient because it has fewer parameters. (2) It has small model size (less than 5 MB), therefore it is easy to implement to embedded system. (3) Applications developed for this network are easy to move and require less communication [19]–[21]. In this research, the pap smear images were classified into three class i.e., normal, low-grade SIL (LSIL), and high-grade SIL (HSIL). We trained the pre-trained SqueezeNet architecture with the three class of pap smear images dataset in caffe. The fine-tuning process was started with the initialization of the model’s features to the object’s broader spectrum. Then, the last layer output number was changed to fit the number of labels for cervical cancer class. We also provided a comparison between our proposed models with other architectures i.e., MobileNet and SeNet. The result showed that the SqueezeNet based model has comparable accuracy and way faster inference speed than MobileNet and SeNet.

2. SQUEEZENET

In order to get an efficient and fast training model, we adopt SqueezeNet, a small - sized CNN based architecture. We use a pre-trained SqueezeNet as a basic model to be trained with three classes instance our cervical cancer image dataset. The pre-trained net act as our base network and we change the final layer output number to predict the class. The SqueezeNet is proven to achieved AlexNet-level accuracy on ImageNet with 50 times fewer parameters and 510 times smaller size [19]. The low parameter count was achieved by implementing three main strategies. First, they employed a 1x1 filter instead of 3x3. Second, they employed the Squeeze layer

to decrease the number of the input channel to the 3x3. The combination of these two strategies composes the fire module, shown in Fig. 1. The third strategy was they had set large activation maps. While the small model’s size was obtained by model compression technique. For the sake of detailed SqueezeNet architecture, please refers to [19]. In this paper, we employ SqueezeNet v1.1. The net architecture comprises of 64 filters 3x3 resolution, and pooling layers in layer 1,3, and 5. To be able to adapt the 3 predictions class, we had changed the last convolution layer output number. The appropriate output of this layer is 3 correspond to the class prediction number.

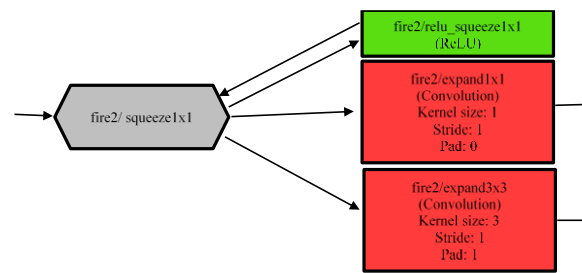


Figure 1. Fire module, a microarchitectural perspective of the SqueezeNet’s component.

3. TRANSFER LEARNING

Deep learning from scratch can be tedious and time-consuming. A limited amount of training data might lead to over-fitted classifiers with poor generalization skills. While collecting a sufficient number of manually labelled training data may prove relatively expensive. Transfer learning can overcome these problems by transferring knowledge from related source domain which has much more data (ImageNet) to help classification in the target domain [22], [23]. Transfer learning from non-medical to medical image domains one of the keys to build an effective CNN models, because it quickly generates the final model with way fewer instance-level annotated training data than the classification task [24], [25]. In our SqueezeNet based model, we pre-trained SqueezeNet with the object dataset ImageNet to give exposure to its feature maps with the general random natural object. Subsequently, we fine-tuned the network to solve the cervical cancer image classification problem. Fine-tuning a CNN model is a procedure based on the concept of transfer learning. Fig. 2 is the visualization of our method to adopt classes. Although our task is significantly different from the originally trained model dataset and there is a possibility of the training data shortage, this practice is believed could extract a meaningful representation of the intended object classification in a limited number of data datasets. The fine-tuning procedure is started with the model’s features initialization to the broader spectrum of the object. After the initialization finished, we replace the last layer of

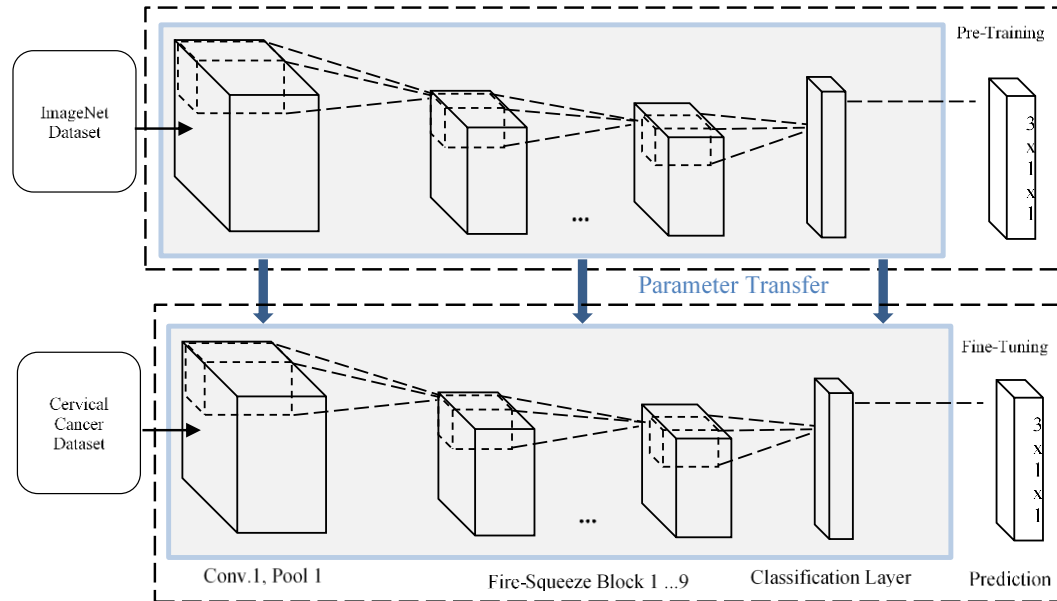


Figure 2. Transfer learning visualization for training cervical cancer images.

SqueezeNet to fit the number of labels for cervical cancer class. This process is expected to minimize errors in a more specific task domain. Under this experimental setup, we investigate and report our blood cell classification task experiment for cervical cancer detection.

4. DATASETS

The softcopy datasets of pap smear images were collected from dr. Soetomo hospital. The data collection was focused on the cancer cell in the squamous epithelium. The data from several stage of cervical cancer severity was collected with the help of specialist doctor. All the collected images were classified into three class i.e., normal, low grade squamous intraepithelial lesion (LSIL), and high grade squamous intraepithelial lesion (HSIL). Then, the images were pre-processed by cropping/ segmenting and resizing. The segmentation was focused on the single cell, it was done manually with the help of the hospital technician. While the resizing process was done automatically to all images at the same time in order to get uniform image's dimension. The augmentation data was done by rotating and flipping the images. A total of 799 images were collected from the pre-processing. The detailed datasets were summarized in Table 1. The training data from all class were merged into one, likewise the test data. Each image then labelled and annotated, then processed in a random manner. The proposed SqueezeNet model then compared to MobileNet and SeNet to get the best model with optimum result. The performance of the software was evaluated by data analysis of accuracy and inference time value. The analysis was done with a confusion matrix.

5. RESULT

The datasets were consisted of 799 images from all classes. A total of 85% of images used as training data and 15% used as test data. All the training data was combined, likewise the test data. The images datasets were pre-processed, augmented, labelled, and annotated in a random manner. The example of classification and pro-processing result is depicted in Fig. 3.

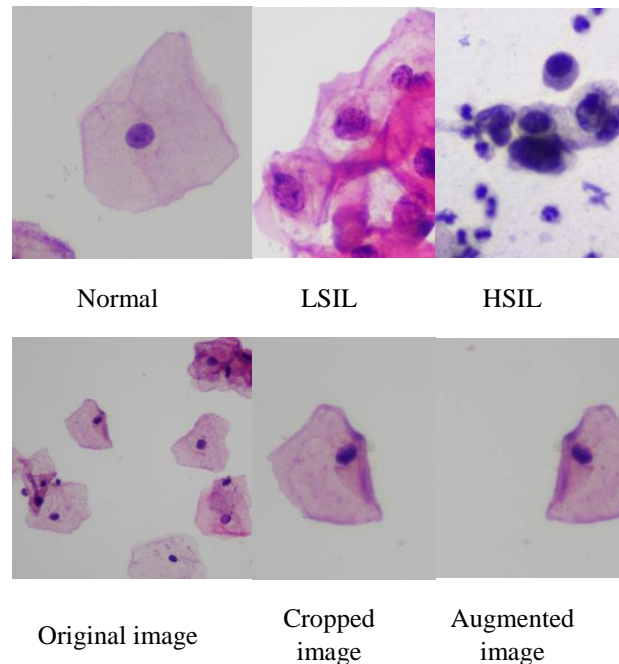


Figure 3. Image classification and preprocessing result.

In this paper, we implement deep network training in Caffe [26], the deep learning machinery that widely known in the computer vision community. Our system built on the GTX 1080 Ti 11 GB GPU platform. The result of the SqueezeNet compact parameters, we able to perform 30,000 iterations in approximately 2 hours training session. We prepared the data in LMDB data format and the standard data augmentation were performed on the fly. We compared our result with 2 other CNN based classification model. Which are MobileNet and SeNet. Figure. 4 describes the SqueezeNet prediction result. 122 test images were deployed to assess the performance of each model. SqueezeNet was able to predict with the average accuracy is 98.41%.

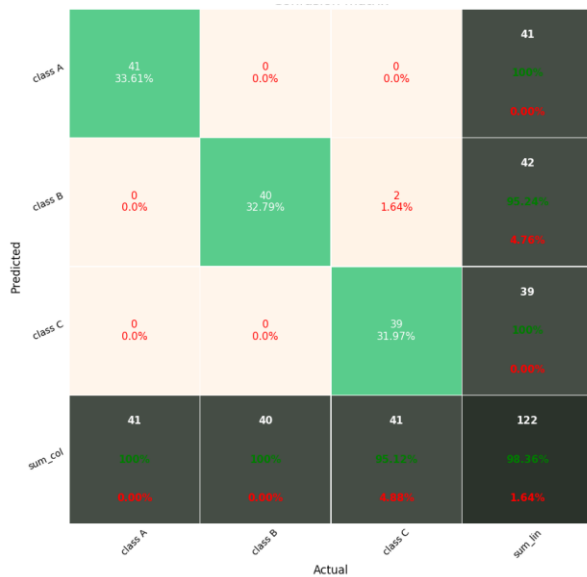


Figure 4. The confusion matrix.

Table 1 shows the per-class prediction accuracy of our SqueezeNet based proposed model with two other comparison models. SqueezeNet gives mistakenly predict at LSIL class, with the accuracy number 95.24%, this number is comparable with the other models. Further, we test the inference speed for all of the models. Table 2 shows SqueezeNet’s inference time compare with two other models. Here, SqueezeNet performed three times faster toward MobileNet and 6 times faster toward SeNet.

Table 1. Comparison of prediction accuracy

Class	SqueezeNet	MobileNet	SeNet
HSIL	100%	100%	100%
LSIL	95.24%	95.24%	97.56%
Normal	100%	100%	100%

Table 2. Comparison of interference speed

	Squeeze	MobileNet	SeNet
Inf. Speed	0.078	0.226	0.439

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