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*Original Article*

# Conditional Super Resolution Generative Adversarial Network for Cervical Cell Image Enhancement

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***Abstract*** *- Abnormal cellular development in the cervix causes cervical cancer. Undergoing Pap smear screening & HPV tests at regular intervals possibly helps identify the disease at an early stage, aiding diagnosis and treatment. Pathologists are involved in the screening to detect abnormal cells in the slide. Removing a portion of the slide with poor quality could improve nuclei detection by enabling better visualization of some important information. In this study, a Conditional Generative Adversarial Network (CGAN) with a Super Resolution technique is applied for cervical cell images to generate photo-realistic images. Poor-quality images are not removed; rather, they are converted into good-quality images. It ensures equal distribution of image generation in terms of classes in a given dataset. The performance of the recommended technique is measured using PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity)and Inception Score(IS). The proposed methodology outperforms other augmentation techniques and Variational Autoencoders (VAE) based algorithms.*

***Keywords*** *- Augmentation, Cervical cells, CGAN, CNN, Super resolution.*

## 1. Introduction

Cervical cancer is the fourth most cancer that causes death among women worldwide. As per WHO report, nearly 279,900 deaths occurred globally in 2018. Human papillomavirus (HPV) plays a major role in developing cancer in the cervix. Among the 14 cancer-inducing HPV types, HPV-16 and HPV-18 cause approximately 70 percentages of cervical cancers and pre-cancerous lesions of the cervix. HPV vaccination prevents HPV infections; early detection through screening tests and timely treatment can cure cancer.

The common diagnostic techniques include Pap smear, Colposcopy, and biopsy. Automatic detection of the pre-cancerous cell using the Deep Learning technique takes less time and is cost-effective. Previous research indicates the support of deep learning techniques for doctors to detect cervical cancer. Nuclei detection plays an important role in the automation of abnormal cell detection. Typically, a single slide contains multiple numbers of overlapped cells, and the nucleus present in the cells helps to identify its type. The massive slide is divided into several images by adapting techniques such as sliding windows, yolo, etc. Images obtained through this technique affect the quality, resulting in poor accuracy. In order to obtain better accuracy, the quality of divided images had to be improved.

CNN model is prominently involved in Education, Healthcare and Industry. Implementing CNN in medical analysis eases the decision-making process. Pap smear test results can be processed with CNN based model. Unlikely, Medical images/datasets are not accessible easily, and sometimes the dataset is tiny in nature. In contrast, CNN requires huge images to train the model, and overfitting is another challenging factor with the existing tiny dataset. This paper applies Conditional Generative Adversarial Network (CGAN) architecture to generate cervical cell images. CGAN has a label as its additional parameter included in both the generator and discriminator. Image Super Resolution process collaborated with CGAN to produce High-Resolution images.

## 2. Literature Study

Goodfellow et al. (2014) proposed a GAN framework using antagonists to enhance the performance of ML algorithms. GAN involves two sub-models, namely, generator and discriminator. The generator model generates images based on the input given, and the result is taken as input to the discriminator. The binary classifier named discriminator predicts whether the generated image is real or fake. Mehdi Mirza and Simon Osindero, 2014 [27] proposed an advanced GAN architecture to estimate generative models through an adversarial procedure. Like GAN, the architecture also has Generator G and Discriminator D. A Convolutional Neural Network takes random noise and labels as input to generate high-quality images and then feeds them into the discriminator. Along with the generated image through CGAN, the label information is also provided as input. The discriminator results in the probability range between 0 and 1 to indicate the original and generated image. In this paper, CGAN is involved in generating cervical cell images as per input class conditionally. The process of bringing back High-Resolution images from Low-Resolution images is known as Super Resolution. High-quality images in the medical field assist doctors in accurately diagnosing and predicting disease.[5] The pros of combining CGAN and Super Resolution in cervical cell images are avoidance of model overfitting and quick & accurate diagnosis of cancerous cells.

Goodfellow et al. (2014) proposed a GAN framework by using antagonists to enhance the performance of ML algorithms. Many researchers started utilizing GAN in a wide range of applications. Radford et al. [6] (2015) suggested CNNs, as applied in deep learning, for the generator model as well as the discriminator model and further applied it to represent images. If the model has a large number of trainable parameters, then deep Convolutional Networks may result in overfitting. The solution to this problem was suggested by Zhu et al. [7] (2018) using GAN for hyperspectral images. Eghbal-zadeh and Widmer [8] (2017) assessed the quality of GAN-generated images. Yang et al. (2018) [9] used Bi-GAN, which uses two generators to detect LncRNA-associated diseases. Chan and Elsheikh (2017) [10] applied the GAN technique to produce geological data in subterranean fields. Poonam Chaudhari, Himanshu Agrawal and KetanKotecha (2020) [12] synthesized an image using modified generator GAN (MG-GAN) on gene expression data.

Wang et al. (2019) [13] recommended an automated classification & segmentation system for cervical cells. Gabor feature, along with SVM, is used to classify the cells by taking shape and texture features into account. The model achieves more than 89% accuracy in classifying typical and cancerous cells. S.R.P Singh et al. [14] applied the genetic algorithm to detect the staging of cervical cancer staging. A model to diagnose HPV – infection cervical cancer was recommended by Guo Chen and| Wenjian Zhang (2021), and the model was constructed using an optimized decision tree. [16] Siyu Chen et al. (2020) proposed a model based on RCGAN(Residual Network and Generative Adversarial Network) to augment a single-cell cervical image. In addition, classification is applied to the augmented image to predict cervical cancer. [17] Ahmed Ghoneim et al. (2020) recommended CNN based model to predict and detect cervical cancer. Further, an extreme learning machine (ELM)-based classifier is applied to classify the input images. [18] Aditya Khamparia et al. (2020) [20] applied deep convolution with a Variational Autoencoders network to predict and classify cervical cancer. Besides Variational Autoencoder's effectiveness, a model achieved better accuracy by setting ReLU as the activation unit and Adam as the optimizer. This research aims to focus on low-quality images in the slide and convert them into high-quality images. The proposed work generates High-Quality images that ease the nuclei detection process for the segmentation and classification of cervical cells.

## 3. Materials and Methods

### *3.1. Dataset Description*

In this paper, the largest cervical cancer dataset (SipakMed) from Kaggle is utilized to augment the cervical cells and classified into five classes using the proposed framework. [25] The number of images for each class in the dataset is given in Table 1.

### *3.2. Discriminator Model*

In the conditional super resolution GAN's discriminator model, the embedding layer is involved in converting an integer encoded value into a vector. Here, the number of classes is 5, and the vector representation of each label is of size 50, followed by the Dense and reshaped layer. Concatenation of label input and image input of size 256*256*4 applied using convolution layer. The model has eight convolutional layers along with batch normalization with the stride of 1 pixel, and the Leaky ReLU is used for the activation. Adam optimizer and binary cross-entropy loss function are utilized, and the VGG loss(Content Loss) is invoked. The second layer of the VGG19 pretrained model takes generated and Super Resolution images as a parameter, and then the loss is calculated.

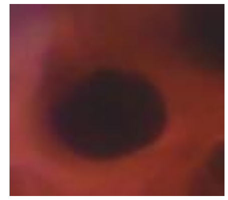
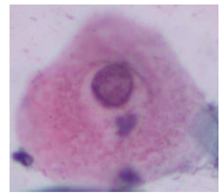
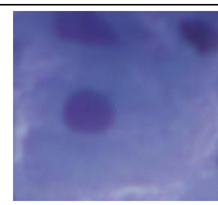
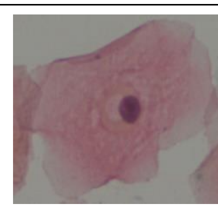
#### *3.2.1. Parameters in Discriminator*

Images are sent to the discriminator model to train the model to discriminate whether the generated image is real or fake. Secondly, a label parameter is added as an additional input layer to condition both generator and the discriminator model. Label parameter ensures an equal number of image generation in terms of class.

#### *3.2.2. Generator Model*

In the generator model, a latent vector, along with the number of the class, is sent as an input. Similar to the discriminator model, it uses an embedding layer, dense layer and reshaped layer. The model initially 4 times downsampled the image and took it as an input layer. Conv2D layer with filter size 64 is applied, followed by 16 residual blocks. The concatenation layer is also involved. Two UpSampling 2D layers with size 2 are involved in improving the resolution of the images. Each Up Sampling 2D layer follows the Conv2D layer with 256 filters and strides as 1.

**Table 1. Classes, number of images and a sample image of each class in the Kaggle dataset**

| Class | Number of Images | Sample Image |
|---|---|---|
| Dyskeratotic | 813 |  |
| Koilocytotic | 825 |  |
| Metaplastic | 793 |  |
| Parabasal | 787 |  |
| Superficial Intermediate | 831 |  |
| **Total Images** | 4049 | |

*3.2.3. Parameters in Generator*

Hyperparameters involved in the Generator model are Low-Resolution Images, Labels and Noise. Generator plays a vital role in generating super-resolution images in our proposed system. A generator function G is trained, whose function is to estimate the corresponding HR image for a given LR input image. Low-resolution images are given in the generator; upscale the images up to twice.

Random noise is provided as input to the generator to generate random samples. In order to generate classes of images equally, both the generator and discriminator are given the label as input. So, the generator equally generates a number of images equally. Hyperparameters of both Generator and Discriminator with their values are given in Table 2.

**Table 2. Parameters in generator and discriminator model**

| Model | Hyper-Parameter | Value |
|---|---|---|
| Generator | Labels | 5 |
| | Noise | Random value |
| | LR image | 256*256*4 |
| Discriminator | Images to train | 256*256*4 |
| | Labels | 5 |

*3.2.4. Architecture of Adversarial Network*

GAN has a Generative model and a Discriminative model. Generative model (G) takes data distribution, and the other model, Discriminative (D), predicts the likelihood of a sample from training data. The main objective of the proposed model is to train Generator G to produce High-Resolution Image($I^{HR}$) from a Low-Resolution Image($I^{LR}$). This can be achieved by training a Generator as a Feed-Forward network $GX_G$ with a parameter of $X_G$ and discriminator of $Y_D$.

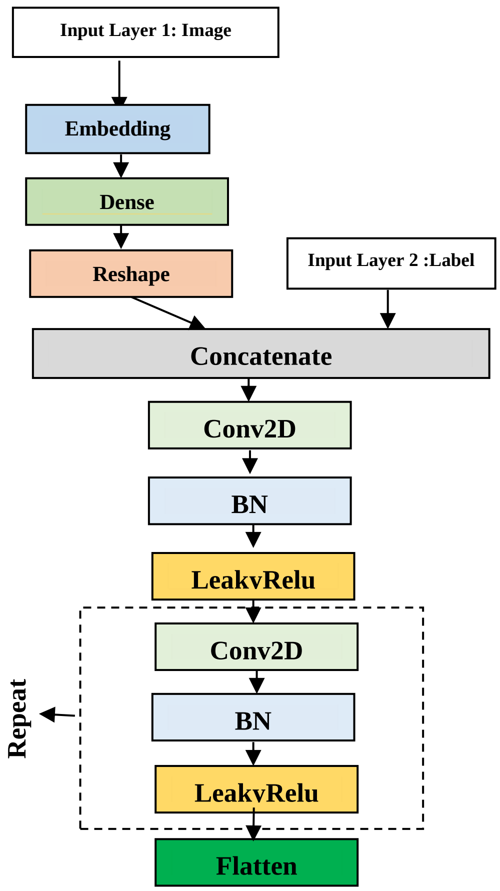



**Fig. 1 Structure of CSRGAN's discriminator**

Following Christian Ledig et al. [5] and Mehdi Mirza et al. [27], a Discriminator and Generator network is defined in order to optimize to solve the min-max problem of adversarial as shown in Equation 1:

$$\min_{X_G} \max_{Y_D} E_{I^{HR}} \sim p_r(I^{HR})[\log DY_D(I^{HR})] + E_{I^{LR}} \sim p_{G,z}(I^{LR})[\log(1-DY_D(GX_G(I^{LR}|z)))] \quad (1)$$

The structure of conditional super resolution adversarial net is shown in Figure 1 and Figure 2.

## 4. Results and Discussion

### *4.1. Metrics*

#### *4.1.1. PSNR*

Peak Signal-to-Noise Ratio is a metric used to determine the quality of the image. The value of PSNR is infinity if the MSE value attains zero, and the value becomes less if the numerical discrepancy between images is high. The formula of PSNR is shown in Equation 2:

$$PSNR = 20 \log_{10} \frac{(MAX_f)}{\sqrt{MSE}} \quad (2)$$

Where, MSE $= \frac{1}{mn} \sum_0^{m-1} \sum_0^{n-1} ||f(i,j) - g(i,j)||^2$

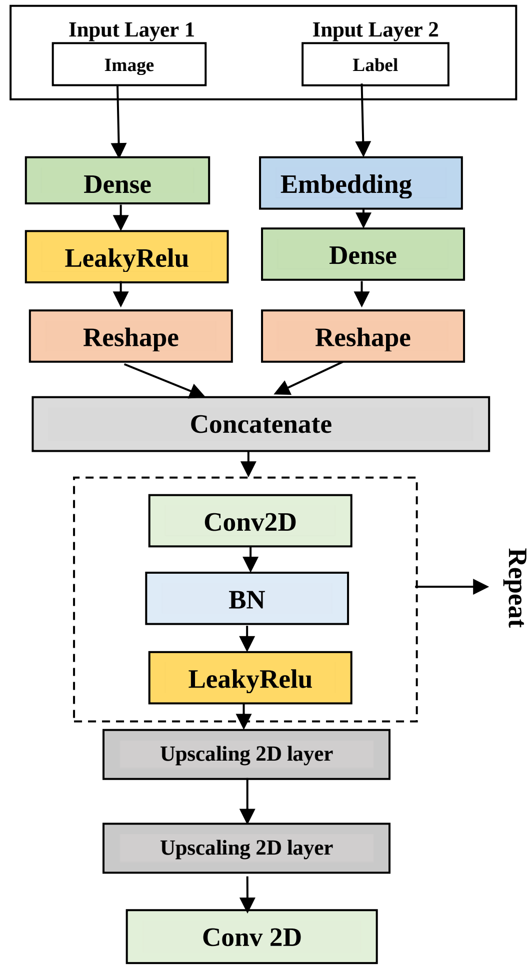



**Fig. 2 Structure of CSRGAN's generator**

Difference between the given two images, f and g, is measured using MSE where i and j are the dimensions of the given images. The maximum pixel value is denoted as MAXfto to find out the PSNR value.

#### *4.1.2. SSIM*

Structural similarity is a familiar metric to evaluate the similarity between the given images. Structural similarity index is estimated on various regions of an image. The formula of SSIM is shown in Equation 3.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma + c_2)}{(\mu_x{}^2 + \mu_y{}^2 + c_1)(\sigma_x{}^2 + \sigma_y{}^2 + c_2)} \quad (3)$$

SSIM formula depends on the Luminance, contrast and structure between x and y samples. The average value of x and y is indicated using µx and µy. Similarly, σx2 and σy2 are the variances of x and y. x and y's covariance is indicated as σxy. In addition, c1 and c2 are two variables involved in balancing the division in case of a weak denominator.

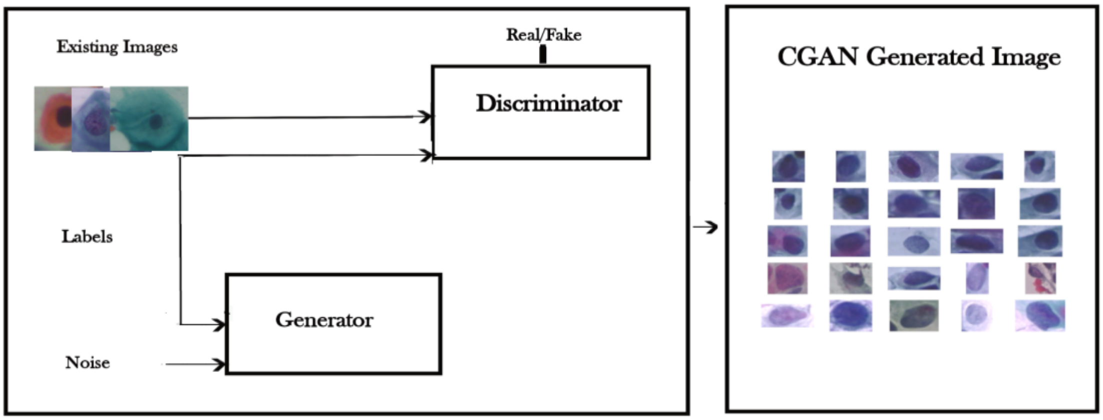



**Fig. 3 Augmented images using conditional GAN**

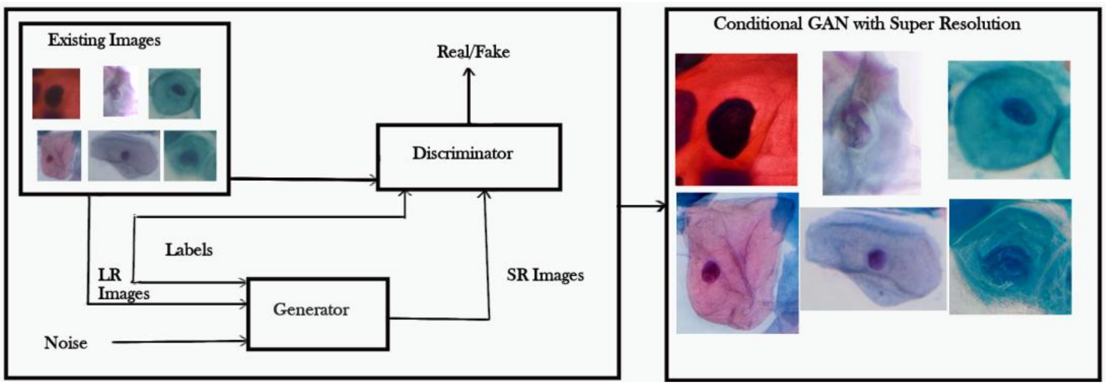



**Fig. 4 Augmented images using conditional super resolution GAN**

*4.1.3. Inception Score*

It is a metric to assess the quality of synthesized images generated by GAN. The augmented images using conditional GAN is shown in Figure 3.

### *4.2. Performance of CSRGAN*

Identifying abnormal cells is dependent on the nucleus present in them. Images with normal and poor quality are taken for quality enhancement. The qualitative performance of CSRGAN can be seen in Figure 4, where the original images given in the dataset and the image generated by CSRGAN are shown. It can be seen in Figure 4 that the generated images look like photo-realistic images when compared to the existing images. The Conditional Super Resolution GAN training set was trained with 100 epochs for synthesising Super Resolution cervical cell images for each of the five categories. Weight has been updated for the generator and discriminator at each epoch for generating Super Resolution images. To determine the quality of the generated images by Conditional Super Resolution GAN, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity(SSIM) are used. The value of PSNR between the original images and generated images is represented in Table 3. It shows that the quality of images generated by CSRGAN is close to the quality of photo-realistic images.

To evaluate the quality of the Super Resolution of the generated images, we use PSNR and SSIM metrics. A comparison of these metrics is shown in Table 4. It clearly reveals that the quality of Super Resolution in the generated image is good compared to the other augmentation techniques considered. Deep Learning techniques in the medical image provides faithful result in terms of predicting diseases. In this paper, cervical cell images are generated using Conditional Super Resolution GAN. In this augmentation technique, Super Resolution is embedded with Conditional GAN and the proposed framework's effectiveness is compared with other algorithms such as Variational Auto Encoders and other augmentation techniques. This data augmentation approach increases the generalizability of the network and secures it from the problem of over-fitting. The proposed model generates Super Resolution images with a PSNR value of 37.72 and an SSIM value of 0.9703. The nuclei detection process can be improved by eliminating the poor-quality images that may obscure some important information. Instead of eliminating or misclassifying, introducing the proposed methodology improves the image's quality and enhances accuracy. The limitation of this technique is, applying it to a slide with high-luminance sections may result in brighter images, which can impact the accuracy of the analysis.

**Table 3. PSNR between original and CSRGAN image**

| Image | PSNR in db |
|---|---|
| Original Image | 27.61 |
| CSRGAN generated image | 29.72 |

**Table 4. Comparison among various algorithms**

| Author | Method | PSNR in db | SSIM | IS |
|---|---|---|---|---|
| Amreen Abbas et al. [3] | CGAN | 28.15 | - | 2.83 |
| Ledig C et al. [5] | SRGAN | 21.15 | 0.6868 | - |
| Kaikai Liu et al, [27] | VAE-SGAN | - | - | 1.78 |
| Proposed Work | CSRGAN | 29.07 | 0.8468 | 2.72 |

## 5. Conclusion

The accuracy of cell categorization is improved by creating photo-realistic cervical cell images using this technique. Instead of removing the poor-quality images, this technique focused on improving the quality of images and avoiding the misclassification of cells. It has been achieved through previous research in this field, and this research explores approaches to Conditional Super Resolution GAN for producing super-resolution images in the same vein. Setting goals for enhancing super-resolution image generation in future research efforts in this field is possible.

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