

# Generating Realistic Blood-Cell Images using Cycle-Consistent Generative Adversarial Networks

M. V. Nageswara Rao



**Abstract:** generative adversarial networks are a neural-network based generative models , predominantly used for generating data-samples close to the data distribution they have been trained on .A model for generating realistic blood cell images based on cycle-consistent generative adversarial networks is developed along with their corresponding segmentation masks

**Index Terms:** GAN, Cycle-Consistency

## I. INTRODUCTION

Hematology is a branch of medicine related to study of to study blood and its related diseases and causing factors. Digital imaging is extensively used most of the tasks involving computational hematology. Most such tasks require segmenting regions of blood cells from the blood-cell images.

Building such a model using machine learning techniques requires richly annotated datasets.

However annotating segmentation masks for blood-cell datasets is a tedious time-consuming task. Apart from that collecting a such a large dataset is not so viable due to the limited availability of images in that domain. This provokes for data-augmentation methods in this task.

Most data-augmentation tasks involve either distorting the given set of images using geometric transformations such as affine transformations or rotating, scaling etc. Or adding additional noise to the images. Such methods for data-augmentation often produce low-quality datasets for training large machine learning models, since most deep-learning based models are often robust to such transformations in data.

Using generative-adversarial networks for data-augmentation became one of the most important techniques in a machine-learning practitioner’s toolkit.

Salome Kazeminaa, Christoph Baurb, Arjan Kuijper , Bram van Ginneken Nassir Navab, Shadi Albarqouni , Anirban Mukhopadhyay provide a comprehensive survey of various generative adversarial network models used for augmenting medical datasets[1].

Andrew Beers James Brown Ken Chang J. Peter Campbel , Susan Ostmo,Michael F. Chiang , Jayashree Kalpathy-Cramer demonstrate a method to generate high-resolution brain-tumor images using progressively growing generative adversarial networks. Each network in this model upscales the resolution of the previously generated image from the previous network model [2].

Oleksandr Bailo, DongShik Ham, and Young Min Shin Noul Inc demonstrate a method to generate near-realistic red-blood-cell images using conditional-generative adversarial networks[pix2pix] and evaluate the augmented dataset based on various segmentation networks [3].

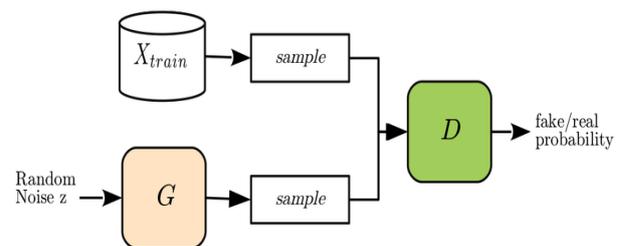
## II. GENERATIVE ADVERSIAL NETWORKS

Generative adversarial networks are neural network based generative models, a basic generative adversarial network consists of two neural networks which are jointly trained to minimize their minimax loss.

The generator network denoted by ‘G’ generates images taking a random noise as input, the discriminator ‘D’ measures the discrepancy between the generated image sample and actual data sample present in the dataset.

Both the generator and discriminator are jointly trained to minimize their minimax loss, so that they converge to produce a generator which generates data-samples almost identical to the actual data, the discriminator can correctly classify the actual data samples from the fake ones.

The theory behind the convergence of generative adversarial networks is inspired by two-player zero sum games in game theory. [4]



## III. CYCLE CONSISTENT GENERATIVE ADVERSIAL NETWORKS

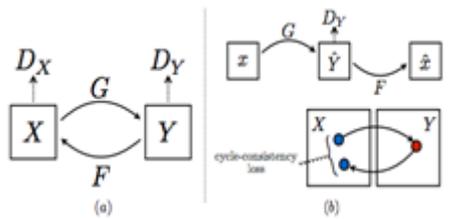
Cycle-consistent generative adversarial network are predominantly used in image-image translation problems, cycle consistency-loss can be considered as a crude measure of image-image analogies. Here two different generative adversarial network model’s ‘G’ and ‘F’ are jointly trained to map the image from set X to set Y and back keeping an.

**Revised Manuscript Received on October 30, 2019.**

\* Correspondence Author

M. V. Nageswara Rao\*, Electronics and Communication Engineering, GMRIIT, Rajam, India. Email:nageswararao.mv@gmrit.edu.in

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](https://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>.



intermediate class in between, the image obtained by converting the given image back to the original set and the discrepancy between both the obtained image and the original one used in mapping is measured by “cycle-consistency loss” which is minimized along with the GAN loss function. As illustrated in the diagram. Thus the total objective function becomes:

$LGAN(G, D_y, X, Y) + LGAN(F, D_x, Y, X) + \lambda L_{cyc}(G, F)$   
 where  $D_x, D_y$  are discriminator networks and  $\lambda$  is regularizing term for the cycle-consistency loss,  $G, F$  are the two generator networks for mapping between classes.

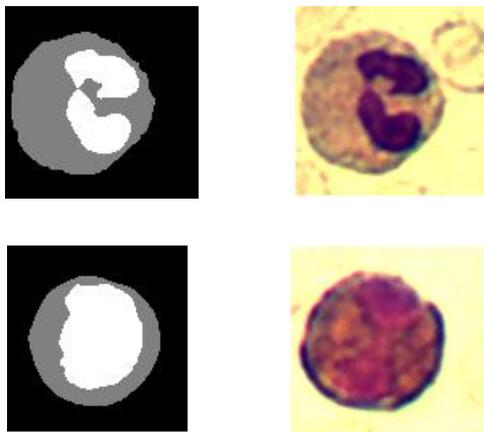
## IV. IMPLEMENTATION

all the model-building and training is done in python using pytorch module, all the images are resized to 256x256 size, the dataset is obtained from jiangxi tecom science corporation which consists of 300 white blood cell images each of 120x120 pixels and color depth of 24 bits. Due to enlargement of size the actual image appears to be blurry compared to the original one which can be avoided by rescaling the images obtained at the end. The generator networks are 9 layered residual networks [5] while the discriminators are inspired patchGAN classifier. Due to computational constraints the model is trained for 100 epochs on the dataset with a learning rate of 0.0002.

## V. RESULTS

The following images are obtained by running the model on the provided segmentation masks, the mask images can be easily generated using any simple paint-program.

ACTUAL MASK                      ACTUAL IMAGE



## VI. CONCLUSION

Implemented the generative adversarial networks successfully to generate realistic blood cell images based on cycle-consistent generative adversarial networks along with their corresponding segmentation masks.

## REFERENCES

1. Salome Kazeminaa, Christoph Baurb, Arjan Kuijperc, Bram van Ginneken, Nassir Navabb, Shadi Albarqounib, Anirban Mukhopadhyaya: GANs for Medical Image Analysis: arXiv, Dec, 2018.
2. Andrew Beers, James Brown, Ken Chang, J. Peter Campbell, Susan Ostmo, Michael F. Chiang and Jayashree Kalpathy-Cramer: High-resolution medical image synthesis using progressively grown generative adversarial networks: arXiv, May 2018.
3. Oleksandr Bailo, DongShik Ham, and Young Min Shin Noul Inc. Red blood cell image generation for data augmentation using Conditional Generative Adversarial Networks. arXiv, May 2019.
4. Jun-Yan Zhu, Taesung Park, Phillip Isola and Alexei A. Efros: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. arXiv, Nov 2018
5. Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio: Generative Adversarial Nets. arXiv, 2014

## AUTHORS PROFILE



**M. V. Nageswara Rao**, received Ph.D from Andhra University 2013. Presently, he is professor, Department of ECE, GMR Institute of Technology, Rajam, A.P; India. His research interests are VLSI and signal processing.