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Retinopathy Image Augmentation Using Robust Generative Adversarial Networks (GANs) : A Review

Rutu Pathak*[1], Dr. Sheshang Degadwala[2], Dhairya Vyas[3]
*[1]Computer Engineering Department, Sigma Institute of Engineering, Vadodara, Gujarat, India
[2]Computer Engineering Department, Sigma Institute of Engineering, Vadodara, Gujarat, India
[3]Managing Director, Shree Drashti Infotech LLP, Vadodara, Gujarat, India

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ABSTRACT

Crimes against women have become a global problem, and many governments are striving to curb them. The National Crime Records Bureau indicates that crimes against women have risen substantially. In June, NCW received the most crime complaints against women in eight months. The Indian government is interested in finding a solution to this problem and promoting social progress. Each year, crime reports generate a vast amount of data, which is collated. This information may help us evaluate and anticipate criminal behavior and reduce criminal activity. Data analysis involves assessing, cleansing, manipulating, and modelling data to draw conclusions and enhance decision-making. This research uses supervision learning to analyze the Indian women's criminal examination. The police department received crime reports. Anomalies, invalid locations, longitudes, and scopes were created in advance. The study was meant to breakdown women's crimes by kind and district and produce crime heat maps. The results help decision makers predict and prevent crimes against women. Applying Find the geographical criminal hotspot and the kind of crime, such as murder, rape, sexual assault, beating, dowry threats by the husband or his family, immoral trafficking, stalking, etc.

Keywords : Crime against women, Data Mining, Region, Machine Learning, Forecasting, Support Vector Machine, K-nearest Neighbor, Random Forest, Decision Tree, Navier Bayes.

I. INTRODUCTION

The overall crime rate has been steadily climbing for quite some time now. Because criminal activity is either methodical or fortuitous, it is impossible to predict it. Crimes committed against women are sometimes referred to as gender-based forms of violence. Acts of criminality that are done against women and girls, either mostly or only. It is a crime that is fast growing at an alarming rate in many regions of the nation in the present day. The purpose of this study is to conduct a survey of the criminal activity that is causing crime against women and to come up with effective preventative methods. As a result, it is imperative to perform an analysis of the various types of data pertaining to crimes committed against women to make projections regarding patterns and trends. This will enable law enforcement officials to take effective measures to reduce the number of crimes committed against women. Here are some examples of many sorts of crimes that may be committed in India, including homicide, rape, sexual assault, battering, dowry threats, cruelty committed by the husband or his family, bringing females into the nation illegally, immoral trafficking, etc.

The application of data mining methods may improve the accuracy, performance, and speed with which crime predictions are made. Mining methods are used to assess criminal trends based on both recently collected data and historical information. Therefore, the primary obstacle that stands in our way is the creation of a better and more effective instrument for the identification of crime patterns, which will allow us to properly identify crime patterns.

Problems Associated with Crime Prediction:

- Increase the amount of information in the criminal record that should be positioned to the left and studied.
- The analysis of in sequence raises concerns given that, in turn, incompatibility and deficiency exist.
- Restrictions on how much may be made by selling criminal records at the beginning of the rule The office of enforcement
- The specificity of the research location must be determined in advance for the agenda to be accurate.

II. LITERATURE STUDY

Sr. No.	Title	Publication-Year	Method	Advantage	Future Work
1	Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms	IEEE Access 2020	Prognosis of Microaneurysm and early diagnostics system for non-proliferative diabetic retinopathy (PMNPDR)	This model improved robustness and stability for image segmentation.	Work with Large data volumes and a high range of applications.
2	Application of generative adversarial networks (GAN) for ophthalmology image domains: a survey	Springer-2022	Generative Adversarial Network	Varies Methods of Generative Adversarial Network is discussed with its applications	By optimizing ophthalmology datasets, GAN approaches may improve pathological ocular condition identification systems.

3	Deep Learning Techniques for Diabetic Retinopathy Classification: A Survey	IEEE Access-2022	supervised learning, self-supervised learning	DL methods for DR detection & classification. scores reported of existing methods.	Ultimately, transformer-based models enable better interpretability for researchers and future work
4	Convolutional Neural Network for Diabetic Retinopathy Detection	IEEE-2021	CNN	Training accuracy from 80% to about 94% is improved up to 30 epochs, and after 30 epochs the accuracy is almost constant at around 96%.	The future scope of this includes the model will be improved and trained on more datasets to be capable of identifying more diseases to help the physician in the clinic and hospitals.
5	Detection of Diabetic Retinopathy and its Classification from the Fundus Images	IEEE-2021	Adaptive Histogram, CNN	Fundus images and classify them into various stages of progress of disease as Normal, Moderate and Proliferative Diabetic Retinopathy (PDR).	Increasing No of images using data augmentation
6	Self-Attention Generative Adversarial Networks	2019	Model-SAGAN	Effective in modelling long-range dependencies. Work with ImageNet Datasets	Not work on medical images.
7	Semi-supervised Segmentation of Lesion from Breast Ultrasound Images with Attentional Generative Adversarial Network	Computer Methods and Programs in Biomedicine-2019	Model- BUS-GAN	BUS-GAN model can achieve higher segmentation accuracy on both the in-house testing dataset and the public dataset.	Burden of a tedious image annotation process and alleviating the subjective influence of physician's experiences in clinical practice.
8	Image Super-Resolution Using Progressive Generative	Computerized Medical Imaging and Graphics-	Model- PGAN	This method gives high quality of images for high scaling factors.	Does not work with image translation or combine factors.

	Adversarial Networks for Medical Image Analysis	2018			
9	MedGAN: Medical image translation using GANs	Elsevier-2019	Model-MedGAN	The Model framework outperformed other similar translation approaches quantitatively and qualitatively across the different task.	Work with MR image only.
10	Unpaired Brain MR-to-CT Synthesis using a Structure-Constrained CycleGAN	IEEE-2018	Model-CycleGAN	CycleGAN are very good image quality approaches that of paired image-to-image translation on many tasks.	Tasks that require substantial geometric changes to the image, such as cat-to-dog translations, usually fail.
11	Data Augmentation For Deep Learning Using Generative Adversarial Networks	IEEE 9th Global Conference on Consumer Electronics (GCCE)-2020	Model- GAN	the quality and accuracy of the results achieved were sufficient	improve the accuracy of image generation from a small amount of data using a GAN to generate images of comparable quality to that of the training dataset.
12	Data Augmentation Powered by Generative Adversarial Networks	IEEE-2021	Model- GAN	increase the quality of few-shot learning face identification by using Generative Adversarial Network-based data augmentation techniques.	By increasing the size and diversity of the real facial dataset, the Predictor's accuracy could increase.

III. DIFFERENT GAN TYPES

A. Generative Adversarial Network [1,2,5,7]

The functioning of the first GAN is shown in figure 1. where the G and D represent different types of neural networks. An arbitrary noise data vector, denoted by z, is provided to G as an input. This vector is sampled from the distributed p. (z).

$$\mathbf{L_D = \max_D Ex_{p(x)}\,[\log D(x)] + Ez_{p(z)}\,[\log(1 - D(G(z)))]} \quad [1]$$

$$L_{G=\min_G} Ez_{p(z)}\,[\log(1 - D(G(z))] \quad [2]$$

G intends to manufacture data that are as close to the genuine ones as is humanly feasible in the hopes that D will be unable to differentiate between the real and the false data. The functions listed above are those used to optimize D and G respectively

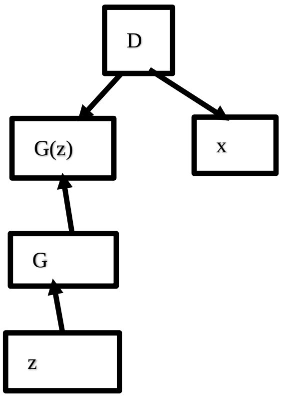

Figure. 1: GAN [7]

B. Deep Convolution Generative Adversarial Network [2]

Because G and D are both ordinary fully connected networks, they are not suitable for use in the production of graphics and so are not included in the original GAN. The distribution of picture data is quite intricate and has a high number of dimensions.

Image creation has been improved because to the development of deep convolutional generative adversarial networks (CNN-GAN), which effectively combined the capabilities of CNNs and GANs. CNNs provide images in a more aesthetically pleasing manner compared to fully linked networks. GAN has a mode collapse problem. The DCGAN recommends a variety of approaches that may be used to strike a healthy balance throughout the training process. Both G and D are examples of fully convolutional neural networks that do down-sampling by use stride convolution rather than a pooling layer.

C. CycleGAN [3, 9]

Pix2pix requires picture pairs, of which at least one must have annotations applied to it; this process consumes a lot of time and results in a considerable financial investment. The Cycle-GAN algorithm recommends using a ring-closed network that consists of two generators and two discriminators. Since there are now two generators and discriminators, the overall structure as well as the flow of data is more complicated than it was in the preceding systems.

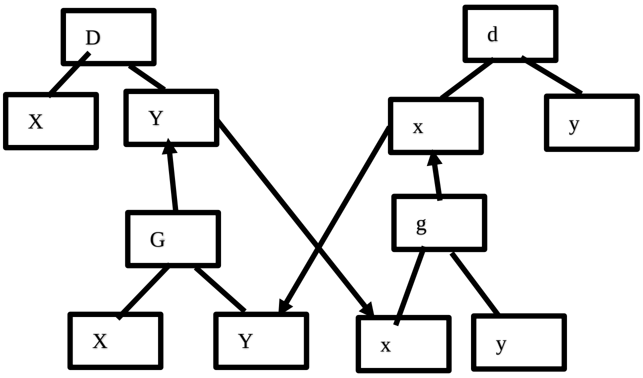

Figure. 2: Cycle-GAN [11]

D. Laplacian Generative Adversarial Network [4,11]

It is not necessary to complete all GAN tasks simultaneously; rather, they may be completed one at a time, which will result in the generation of a whole picture in phases. Replication and the use of residual pictures are the two LAPGAN qualities that, when combined, significantly cut down on the quantity of material and level of complexity that GAN needs to" learn.

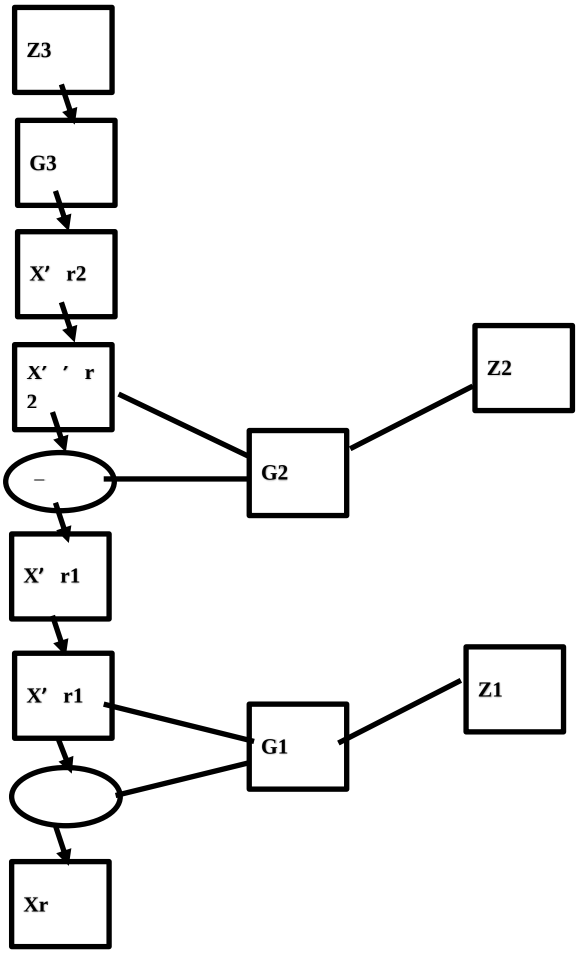

Figure. 3: LAPGAN [1]

E. Conditional Generative Adversarial Network [19,22]

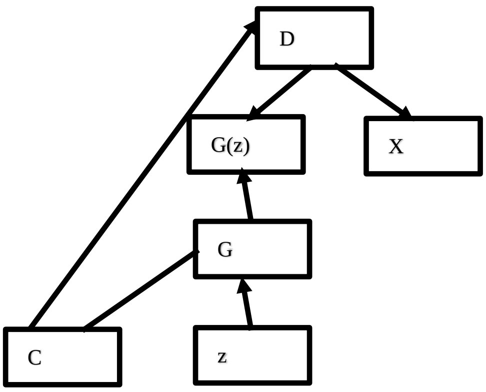

Figure 4: CGAN [12]

To create high-dimensional image data, GAN utilizes a random noise vector with a very small dimension. There are too many degrees of freedom in this approach. Conditional generative adversarial networks improve controllability by introducing a constraint c to data that is a component of both G and D's input layer and directs the production of" data.

IV.Comparative Analysis

TABLE I

COMPARATIVE ANALYSIS OF GANS

Type	Acc	Epoch	Parameters	Limitation
GAN [1,3,5,13,14]	90.2 %	100	sensitivity, specificity, AUC	To determine whether other systems function works as well as the one being utilized, more research is required.
DCGAN [2,21]	91.7 %	90	Accuracy	extend the current network architecture to automatically identify other blood cells in addition to WBCs.

Cycle GAN [1,11, 20]	86.6 %	40-80	Accuracy, FID score	The lack of easily available real-world picture datasets that have been annotated to a high standard is a substantial challenge for the fields of medical image processing and machine learning.
Med GAN [6,10, 18,19, 21]	84.57 %	60	Mean score	More research should be done to classify various medical image
WaveGAN [15, 16, 17, 22]	79%	50	Accuracy, Precision	More research and investigations are required in the areas of COVID-19 and the pandemic to evaluate the potential for a non-contact audio or speech-based diagnosis. This is necessary for the purpose of analyzing the possibilities.

V. CONCLUSION

This study is oriented to GAN for Retinopathy imaging, lists the standard GAN techniques for medical image synthesis. The difficulties with datasets, training techniques, dependability, and mode collapse are highlighted.

The requirement for GANs that are more suited for medical imaging, clinical demands that have advanced, and future directions of unsupervised learning are also covered. It is obvious that GAN offers significant potential and growth opportunities in medical imaging.

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