DCGAN IN AUGMENTING ALGORITHM ANALYSIS DATASET AND SCARCITY CLASSIFICATION

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Abstract— **In This study explores around the impact of using the Deep Convoluted Generative Adversarial Networks (DCGANs) to tackle the problem of class imbalance in image related data, furthermore using the DCGAN is the algorithmic analysis in optimization of data computing in scarcity analysis or classification. Class imbalance inimage dataset has been a severe problem and leads to significant challenge for deep learning model's performance. Using the introduction of imbalance within the dataset, GAN models can generate and utilize the synthetic data. The study looks on how using the integrated GAN-generated images can affect the performance of model, and focusing on improving and enhancing the overall accuracy of model classification by resolving balancing.Results prove that GAN-based data augmentation influences the model training and classification outcomes, showing potential benefits of using GANs for handling the imbalance data in machine learning models qubits.**

Keywords— **AI, DCGAN, Imbalance Dataset, InceptionV3, MobileNet, ResNet50, VGG16**

I. INTRODUCTION

The recent years Generative AI has flourished with rapid advancements, particularly in fields of image and text generation. It has come a long way since release of latent diffusion [1] to stable diffusion today. Many more such models like DALLE2

[2] define what can be achieved through available technology. The problem that plagues this development pace in the field is the imbalanced or incomplete datasets. This leads to biased models and poor performance. Scarce data problem is another such obstacle, which needs to be overcome before successful training for models. In this context, this article sets out to see if state of the art Generative Adversarial Networks can help mitigate the data imbalance and scarce data problem.

This research tackles two critical roadblocks in developing powerful Generative AI: Imbalanced and incomplete datasets. These limitations can lead to biased and unreliable AI models in fig 1. To address these issues, the study explores the potential Gen- erative Adversarial Networks. GAN involves two competing AI systems; The process of making the analysis in the form of the create realistic data based on the existing (incomplete) dataset, while the discriminator tries to identify the generated data as fake. Through this competitive process, both systems improve. The goal is for the generator to learn to create high-quality data even with limitations in the original dataset.

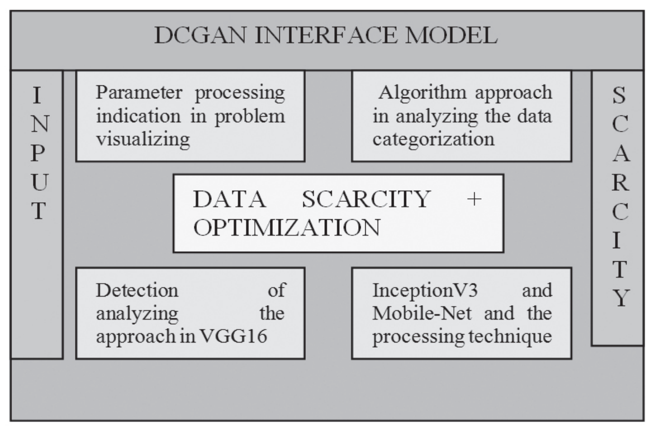

Fig.1 Gathering analysis

This paper estimates the analysis of the cryptographic analysis on the various dataset by implementing the data in the form of Qubits and the analysis of the processing techniques that can estimates analysis of DCGAN scarcity analysis . This algorithmic analysis can be taken to enhances the flexibility and scalability and the optimization while computing the data scarcity in fig 1.

II. LITERATURE SURVEY

[1,2,3] The details provided by J. J. Bird and A. Lofti in [3] showed a new method proposed to understand and recognize the AI- generated images using the computer vision technology. They proposed a CNN model in which they classify images as – Real images and Fake images. The model is trained in such a way that it can identify any visions. This new optimal technology can obtain an accuracy of 92.98% during classification.

In the study of [4], D. Shah et al. focuses on using synthetic mammogram images to improve and amplify and the authenticity. The proposed analysis follows DCGANs to obtain the task by producing high-defined and realistic images. So, this is a profound discovery as it greatly enhances the performance of CNN models on synthetic images during breast cancer detection.

A comprehensive survey [5] on different GAN enabled techniques have been discussed in the work of Christine Dewi. The paper presents different approaches of theory, algorithms, and practical applications. The study also highlights the benefits and drawbacks of different GAN models and also the limitations to why achieving successful implementations of GANs in varieties of application domains.

The recent discovery on MRI image slices discovered [6] by Mourad D., & Oseni K.O. identifies the use of DCGANs to produce high-fidelity and realistic images. The generated slices enhance the datasets and enable ideas of implementing data augmentation while training the deep neural network models, thus MRI data cleaning becomes much easier.

Mukesh C., Likhita A., Yamini A., uses in their study [7] to identify the presence of crevices and cracks on the surface. The detection model discovered InceptionV3 and VGG16 and ResNet50.In the work [8] of Christine Dewi et al., different GAN models are used like Least Squares GANs, Deep Convoluted GANs, and Wasserstein GANs to construct the intrinsic im- ages. The study focusses on algorithm approach to analyses the hidden layer approach in detecting the formation of using different parameters.

Another novel approach proposed in the research of [9] Islam J., Zhang Y., which focusses on generating synthetic medical images using the GAN models. The introduced inno- vation describes that the model can create brain PET images the detection of the analysis.

It provides the en- hancement techniques for the improvement of contrast protein images. They proposed a technique [10] to use the generative adversarial networks by using synthetic images to modify and improve the CNN based results. On comparing synthetic data augmentation to classical data augmentation was established and analysis of the scarcity.

III. METHODOLOGY

The dataset utilized in this study originates from the DPhi Data Sprint #25: Flower Recognition competition. It comprises raw JPEG images of five distinct types of flowers that can be taken as a token for the detection [10] 2492 images, each flower category contributing to the following distribution:

The Daisy category contains 489 images, the Dandelion category contains 559 images, the Rose category contains 468 images, the Sunflower category contains 473 images, and the Tulip category contains 503 images.

A. Dataset Selection

The selection of the Kaggle Flowers dataset for GAN-based image generation was made after analysing following advantages:

- **Diverse Classes:** The dataset consists of 5 flowers each have their unique visual features like shape, structure, colour etc. Due to this diverse nature GAN model van able to learn and understand different and complex patterns and nuances from each flower category.
- **Realistic Variation:** The dataset images have different lighting conditions, understandable backgrounds, and orientations, which reflect the true beauty of photography in nature. This realistic challenges forces GAN to learn robust data distribution for the images with different contexts and settings.

It is the analysis of the approach are a type of framework used in machine learning approach to generate new data that looks similar to the set of training data. The model fake data that resembles the training and the discriminator job is to tell apart real data from the analyses. As the generator gets better at making fake data, the discriminator in fig 2.

Fig. 2. Visualization of Flower Images: Random Sampling from Database

telling it apart from real , is for that's so convincing that the discriminator can't tell the difference between real and fake. The equilibrium point is when the generator creates fakes that are appetent from real data, and the not approach the access of can't confidently say whether image is real or fake. The GAN loss function, denoted as $min_G max_D V(D, G)$ captures this adversarial relationship.

B. DCGAN

DCGAN is an augmentation of the GAN architecture that emphasizes the utilization transposed in both the discriminator and generator components. In the DCGAN framework, the discriminator comprises of convolutions with striding, batch normalization operations, and Leaky ReLU activation functions. It accepts input images of dimensions 3x64x64 and produces a singular scalar value denoting the likelihood that the input image belongs to genuine data distribution in fig 3,4. Conversely, the algorithmic analysis consists of input of the problem statement on the bases of the transpose layer approach in each parameter as input and produces a 3x54x54 RGB image. The CNN layers serve to con- vert the latent vector into a volume with the identical structure of an image, thereby creating lifelike images from stochastic noise.

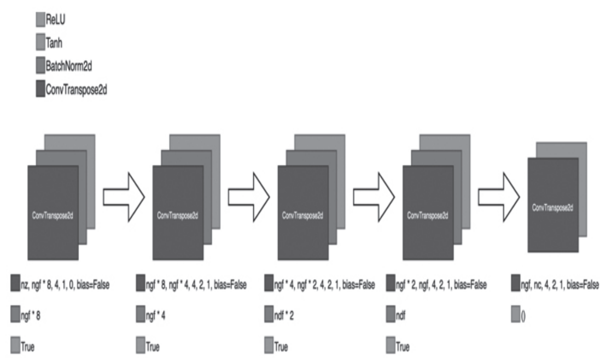

Fig. 3. Generator

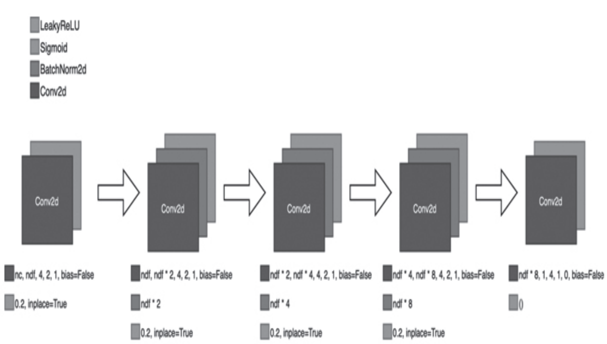

Fig. 4. Discriminator

C. Loss Functions and Optimizers

For our implementation of DCGAN, we have utilized the algorithmic Entropy loss function. This loss function is common employed in adversarial learning scenarios like GANs. It disparity make the distinction of two approach analysis in one system view approach depicting whether an image is real or fake in the context of DCGAN.

$$K(A, B) = K = \{K_1, ..., K_N\}^T$$

$$K_n = -\ [B_n \cdot \log(A_n) + (1 - B_n) \cdot \log(1 - A_n)]$$

D. Train-Set of DCGAN

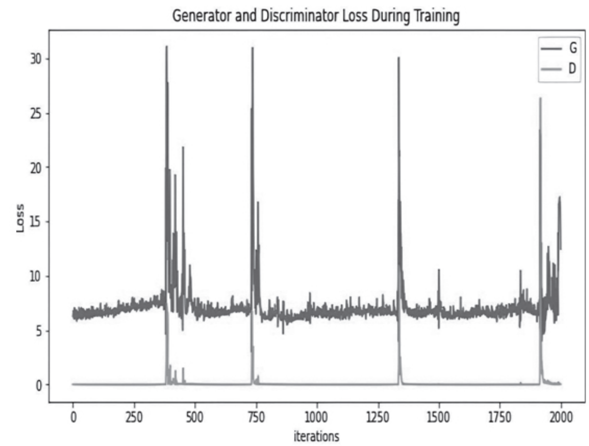

Fig. 5. Loss During Training

The DCGAN model was trained using the following parameters: batch size : 138. Image size: 54x54, Number of Channell4: 3, Size of Latent Vector: 101, Size of parameter Generator: 54, Size of authentication: 54, Trainings Epochs: 2001, Learning Rate: 0.0002, Beta1 Adam Optimizer: 0.5 in fig 5.

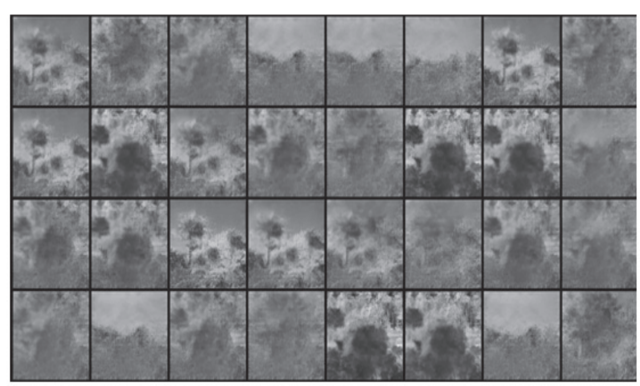

Fig. 6. Image Generated by Generator

Study consists of training the flower image dataset on the following four models - Inceptionv3, MobileNet, Resnet50, VGG16. The intial training of the models involved utilizing a dataset without DCGAN generated images, and relevant metrics were recorded. Subsequently, an imbalance was manually introduced within the sunflower class. To address this imbalance, a DCGAN was trained specifically on the sunflower class, generating additional images. These generated images were then incorporated into the dataset to rectify the imbalance. Following the augmentation of the dataset with DCGAN-generated images, the models were retrained. A comparative analysis was conducted between the performance metrics of the models before and after the inclusion of DCGAN-generated images in fig 6.

E nceptionV3

InceptionV3, proposed by [11] Szegedy et al. in 2015, it convolution neural ar- chitecture. InceptionV3 comprises multiple inception modules that enable efficient feature extraction at various scales. The network architecture includes convolution layers of different filter sizes, including 1x1, 3x3, and 5x5, allowing it to cap- ture both local and global features effectively. Additionally, it incorporates parallel convolutional pathways to maximize information flow in fig 7.

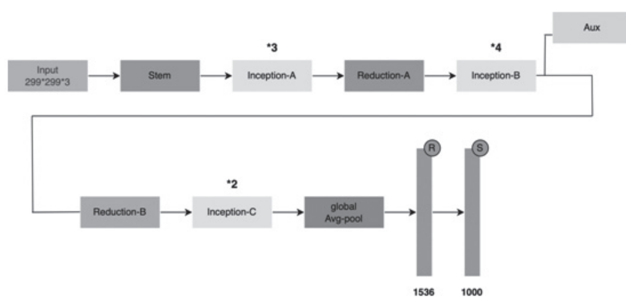

Fig. 7. InceptionV3 Architecture

F. ResNet50

ResNet50, proposed by [13] ResNet50 consists of 40 layers, featuring residual connections that facilitate training of very deep networks. These connections authentication of the network to learn residual map- pings, which helps alleviate the training and testing the layer each by each of deeper models. ResNet50 widely used in various computer visions tasks and servers as a strong baseline in fig 8.

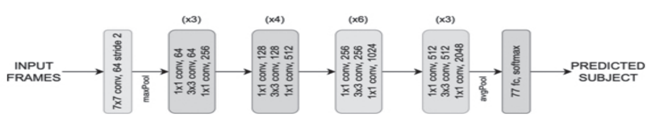

Fig. 8. ResNet50 Architecture

G. VGG16

VGG16, proposed by [14] is the phenomenon approach by which it can be taken in the form of the input layer and cab be gathered in the simultaneously approach of the analysis in the form CNN transpose layer approach as an primary adjustment we made was changing the final layers to accommodate the five classes in our dataset, alongside preprocessing steps such as image transformation and data augmentation in fig 9.

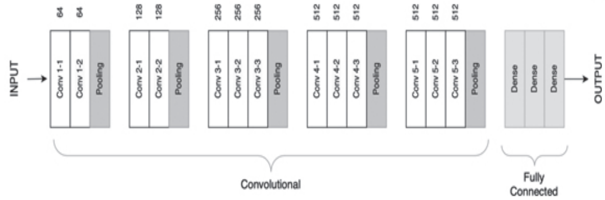

Fig. 9. VGG16 Architecture

IV. MODEL SELECTION

Dataset The chosen models, VGG16, Mobile-Net, ResNet50, and In- ceptionV3, reflect different with its deep stack of simple convolutional layers, tends to have a high parameter count, suitable for detailed feature extraction tasks. Mobile-Net, employs depth wise separable convolutions, which achieves efficiency with fewer parameters, ideal for scarce resource environments. ResNet50 introduces residual connections, with the analysis of the computation approach in analyzing the with relatively fewer parameters, ensuring strong performance across various tasks. InceptionV3, utilizes inception modules to efficiently capture features at many scales. This diverse selection allows for comprehensive testing in various environments enabling a wider, in-depth analysis .Algorithm Analysis.

V. MODEL ANALYSIS

A. InceptionV3

As studied from Fig 10,11 the results depicted that the training accuracy obtained with and without GAN model reaches about 0.90 but the validation accuracy outperforms the results after the use of GAN model as it reaches around 0.85 where the validation accuracy before applying GAN can only reaches up to 0.75. The training loss of the model before applying GAN reaches 0.20 but after applying GAN, it only reaches about 0.30 as Early Stopping initiated. But the validation loss outperforms the results after the use of GAN as it reduces to 0.60 but the original validation loss is about 1.00.

B. MobileNet

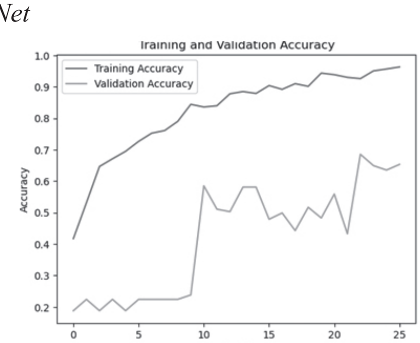

Fig. 10. Acc vs Val Acc for MobileNet Model

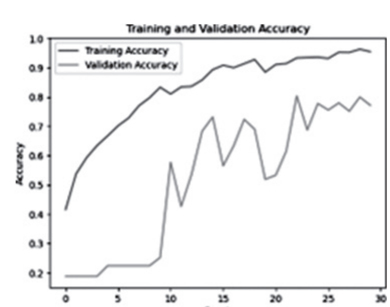

Fig. 11. Acc vs Val Acc for MobileNet Model (with GAN)

the results depicted that the train- ing accuracy obtained with model reaches 0.96 and without GAN model reaches about 0.95 but the validation accuracy outperforms the results after the use of GAN model as it reaches around 0.78 where the validation accuracy before applying GAN can only reaches up to 0.65. The training loss of the model before applying GAN reaches 0.15 but after applying GAN, it only reaches about 0.10 as Early Stopping initiated. But the validation loss outperforms the results after the use of GAN as it reduces to 0.98.

VI. COMPARATIVE ANALYSIS

TABLE I: MODEL WITHOUT GAN GENERATED IMAGES [5,6]

Model	*Accuracy*	*Loss*	*Precision*	*Recall*	*F1 Score*
InceptionV3	0.75	0.2185	0.76	0.75	0.75
MobileNet	0.65	0.1496	0.69	0.65	0.65
ResNet50	0.58	0.2214	0.69	0.58	0.57
VGG16	0.22	1.6079	0.05	0.22	0.08

TABLE II :MODEL PERFORMANCE METRICS WITH GAN GENERATED IMAGES [7,8]

Model	*Accuracy*	*Loss*	*Precision*	*Recall*	*F1 Score*
InceptionV3	0.89	0.3098	0.9	0.9	0.89
MobileNet	0.82	0.109	0.85	0.82	0.82
ResNet50	0.71	0.459	0.78	0.71	0.7
VGG16	0.24	1.5823	0.05	0.23	0.07

All these comparative analysis can be taken from the data parameter to detect and analysis the computing architectural analysis in different types data to optimize and flexible the data set to enhance its compatibility and parameter analysis in table 1,2.

VII. CONCLUSION

In this research, effectiveness of using GAN is addressed with respect to class imbalance for the image datasets and its impact is being tested on deep learning models. The study focuses on using 'Flower' dataset comprising 5 classes – Daisy, Dandelion, Rose, Sunflower, Tulip to classify them using the 4 popular neural network architectures – InceptionV3, MobileNet, ResNet50, VGG16. Also imbalance is imbalance is artificially created in the Sunflower dataset and its images are reduced 75, To rectify the imbalance Deep Convolution GAN model is used to generate synthetic images. These GAN-generated images were then incorporated into the dataset, the models were retrained. During the evaluation process, a comparative analysis of model's performance before after applying GAN has been evaluated. The performance of classification models is tested on the augmented dataset, the study shows that there are significant improvements in various performance metrics exhibiting higher. Remarkably, the validation accuracy and validation loss have been enhanced, indicating the improvements of synthetic data in model generalization, indicating more effective parameter optimization during training. However, it is to be noted that VGG16 model even after the use of GAN-generated data, shown minimal changes, emphasizing that the architecture of VGG16 is not compatible for the GAN generated dataset. In conclusion, the research proves that the efficacy of GANs can be used to handle class in image datasets, leading to improved results for deep learning models. This approach can be used to improve the robustness and effectiveness of the AI models in handling imbalanced data, although the results and performance vary depending on dataset characteristics of the data analysis in quantum learning approach.

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