Data Augmentation of Images Using Generative Adversarial Networks (GANs)

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Abstract

Data augmentation is a crucial technique in machine learning and computer vision, particularly in domains with limited data availability. In the industrial sector, where data collection can be challenging and expensive, data augmentation plays a vital role in overcoming the scarcity of labeled data. This article explores the use of Generative Adversarial Networks (GANs) for data augmentation of images. GANs have shown remarkable success in generating realistic and diverse synthetic data, making them an ideal choice for addressing data scarcity issues. By training a GAN on existing data and generating new samples, we can significantly expand the dataset and improve the performance of various computer vision tasks. This article discusses the motivations behind using GANs for data augmentation, the GAN architecture, training process, and popular augmentation techniques. Additionally, we delve into the challenges and potential applications of GAN-based data augmentation in the industrial sector, highlighting its impact on improving model generalization and performance.

1 Introduction

In recent years, machine learning and computer vision applications have achieved remarkable progress, largely due to advancements in deep learning algorithms and the availability of large-scale labeled datasets. However, in many domains, including the industrial sector, obtaining a substantial amount of annotated data remains a significant challenge. Limited data availability often leads to models with poor generalization and suboptimal performance.

Data augmentation techniques offer a potential solution to mitigate the scarcity of labeled data. These techniques involve applying various transformations, such as rotations, translations, and flips, to existing data samples, thereby increasing the diversity and quantity of the dataset. However, traditional data augmentation methods have limitations in capturing complex data distributions and generating high-quality synthetic samples.

Generative Adversarial Networks (GANs) have emerged as a powerful tool for generating realistic synthetic data. GANs consist of two components: a generator network that learns to generate synthetic samples, and a discriminator network that distinguishes between real and fake data. Through an adversarial training process, GANs can produce highly realistic samples that are indistinguishable from the real data.

This article focuses on the application of GANs for data augmentation in the context of industrial sectors. By training a GAN on available data, we can generate additional synthetic samples that capture the underlying data distribution. These augmented samples can then be used to train machine learning models, enhancing their ability to generalize and perform well on unseen data.

We discuss the architecture and training process of GANs, including popular variants such as Deep Convolutional GANs (DCGANs) and Progressive Growing of GANs (PGGANs). Furthermore, we explore various augmentation techniques enabled by GANs, such as style transfer, image-to-image translation, and conditional generation.

Additionally, we address the challenges associated with GAN-based data augmentation, such as mode collapse and instability during training, and propose potential solutions. We also examine the benefits of GAN-based data augmentation in the industrial sector, where limited data availability hampers the development of robust machine learning models.

Overall, this article aims to provide a comprehensive understanding of data augmentation using GANs, highlighting its potential to address data scarcity challenges in the industrial sector. By leveraging GAN-based augmentation techniques, organizations can enhance their ability to develop accurate

and reliable computer vision systems, paving the way for improved efficiency, quality control, and decision-making in industrial applications.

2 Related work

In essence, this report extends prior research by focusing on the generation of synthetic images for data augmentation, with a particular emphasis on addressing the needs of the industrial sector. In this section, we provide a comprehensive review of recent literature pertaining to data augmentation techniques for industrial image datasets and feature generation networks.

The authors in [3] used a Multi-Class Image Classification GANs to generate synthetic images for the purpose of data augmentation. Further, the authors in [4] have DCGAN to generate high quality synthetic images. Also, we emphasize on the work in [5], where the training improvement of GANs leads to better detection of anomalies. Although the work in [3] focuses on Pneumonia and COVID-19 in chest X-ray images, our hypothesis is that their methodology would be very beneficial to our datasets with class imbalance and it could lead to very amazing results.

Consequently, our work aims to address the challenge of data diversity in the industrial sector by proposing a method to generate class-conditioned training samples. We accomplish this by synthesizing image features based on specific class labels. As such, we view our approach as a novel application within the industrial domain.

2.1 Simple Data Augmentation Techniques

In this section, we explore widely used basic data augmentation techniques for images. These techniques operate on various attributes of individual images to create new images. They require less computational power, are straightforward to implement, and have fast execution times.

Color Inversion: This technique swaps the color values for specific colors in an image to generate new variations. For instance, a black drawing on a white screen would become a white drawing on a black screen.

Color Jittering: This method introduces small random variations in color saturation, brightness, and contrast within the image color space.

Cropping: In this technique, a random or selected section of the original image is cropped and resized to the original size or a specific resolution. Random crop selects a random location for cropping, while center crop focuses on cropping the image at its center.

Flipping: This technique involves flipping the image horizontally or vertically to create a mirrored version.

Gaussian Noise: By adding noise to the RGB channels of each pixel in the image based on the 2D color distribution, a new image is generated.

Grayscale: This method converts the image to grayscale using one to three channels. Random grayscale randomly applies grayscale conversion to the image with a certain probability.

Kernel Filters: Kernel filters, widely used in Computer Vision, involve sliding an NxN matrix called a kernel across an image to perform operations such as blurring or sharpening.

Pad: The pad technique adds padding to the image using a specified pad value.

PCA Jittering: This method applies Principal Component Analysis (PCA) to the image, extracting the principal component, and then adds it to the original image with a Gaussian disturbance of (0, 0.1) to generate a new image.

Random Affine: An affine transformation is a function that preserves points, straight lines, and planes. Random affine transformation applies a random transformation while keeping the center of the image invariant.

Random Erase: This technique randomly selects a rectangular area within the image and sets the pixels within that area to random RGB values. The selected area must include less than 50% of all pixels.

Random Perspective: Random perspective transformation is applied to the image with a given probability, altering the perspective view.

Rotation: The image is rotated randomly within a maximum range of $\pm 25^{\circ}$ to avoid removing important class features. Extreme rotation angles can result in highly distorted and unrealistic images.

Scale: Scaling refers to resizing the image either outward or inward. Outward scaling results in a larger image size compared to the original image.

Shear: This technique stretches and skews the image along the axial planes, with a maximum shear angle of $\pm 20^\circ$ to preserve class characteristics.

Skew Tilt: This technique tilts the image forwards, backwards, left, or right, with a maximum tilt angle of 22.5°. This creates an illusion of the image being viewed from different perspectives.

Translation: Translation involves shifting the image along one or both axes.

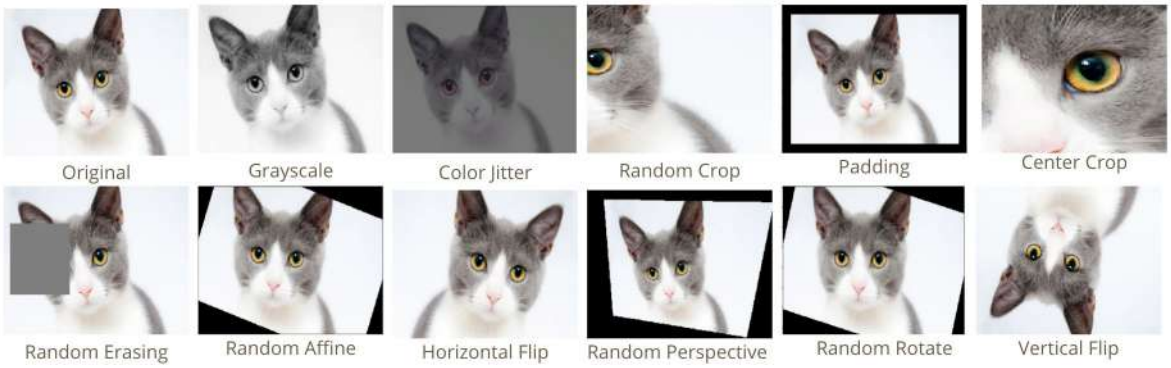

Figure 1: Simple Image Augmentation Techniques.

2.2 Complex Data Augmentation Techniques

In this section, we delve into advanced techniques for augmenting image data, which involve working with multiple images to enhance the dataset. These techniques typically demand substantial computational power and longer execution times.

AutoAugment: AutoAugment is a method that offers an automated approach to search for improved data augmentation policies. Each policy is divided into multiple sub-policies and applied to each image in a mini-batch. The sub-policies consist of image processing functions, such as translation, rotation, or shearing, along with their corresponding probabilities and magnitudes. A search algorithm is employed to find the best policy that yields the highest validation accuracy for a target dataset.

Feature space Augmentation: This technique utilizes neural networks to map high-dimensional inputs to lower-dimensional representations. Manipulations are performed on these lower-level representations, and the vectors are then reconstructed to generate high-dimensional images.

Population Based Augmentation (PBA): PBA is a novel formulation of data augmentation search that efficiently learns the best augmentation policy schedules. Instead of a fixed augmentation policy, PBA generates non-stationary augmentation policy schedules. It leverages the Population Based Training algorithm to determine the augmentation schedule, which defines the best augmentation policy for each epoch of training. The augmentation policy evolves with each epoch.

Neural Style Transfer: Neural Style Transfer manipulates image representations created by CNNs to transfer the style of one image to another while preserving the content of the original image. Although this technique is primarily used for artistic creation, it has limited scientific applications for data augmentation.

GAN-based Data Augmentation: Generative Adversarial Networks (GANs) are a powerful class of neural networks used for unsupervised learning. GANs consist of two competing neural network models that analyze, capture, and replicate the variations within a dataset. These techniques employ generative modeling to augment datasets.

DCGAN (Deep Convolutional GAN) is a widely used technique for image augmentation. It is a variant of conditional GAN that incorporates topological constraints. DCGAN aims to overcome scalability challenges in GANs by substituting pooling layers with strided convolutions and eliminating hidden layers entirely. DCGAN employs a distinctive approach to propagate error from one convolutional layer to the next, resulting in reduced execution time for the algorithm.

CycleGAN (Cycle Consistent Generative Adversarial Networks) is an unsupervised deep learning technique for image-to-image translation and style transfer. It learns mappings between two domains

without paired training data. By incorporating cycle consistency loss and utilizing convolutional and residual blocks, CycleGAN generates realistic and domain-consistent images. It employs patch discriminators to provide feedback for improved outputs. CycleGAN enables various applications such as style transfer and domain adaptation.

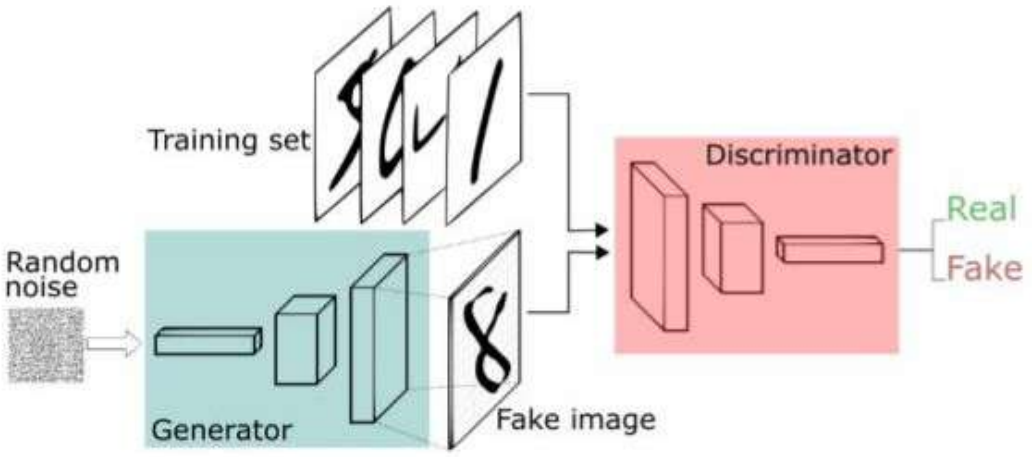

Figure 2: Simple GAN Architecture.

3 Adopted Architectures

Generative Adversarial Networks (GANs) consist of a generator G and a discriminator D that are simultaneously trained with competing goals: The generator G is trained to generate samples that can 'fool' a discriminator D, while the discriminator is trained to classify its inputs as either real (coming from the training dataset) or fake (coming from the samples of G). This competition leads to a minmax formulation with a value function:

$$\min_{\theta_G} \max_{\theta_D} \Big(\mathrm{E}_{\boldsymbol{x} \sim p_{data}(x)} [\log(D(\boldsymbol{x}; \theta_D))] + \mathrm{E}_{\boldsymbol{z} \sim p_z(z)} [\log(1 - D(G(\boldsymbol{z}; \theta_G); \theta_D))] \Big), \tag{1}$$

3.1 Deep Convolutional GAN Architecture

Historical attempts to scale up GANs using CNNs for image modeling have been unsuccessful. This led the authors of LAPGAN (Denton et al., 2015) to develop an alternative approach that iteratively upscales low-resolution generated images, addressing the reliability issues. Similar difficulties were encountered in our own attempts to scale GANs using commonly used CNN architectures in supervised learning. However, through extensive model exploration, a family of architectures was identified that resulted in stable training across various datasets, allowing for the training of higher resolution and deeper generative models.

Core to the approach is the adoption and modification of three recent changes in CNN architectures. The first change involves using all convolutional nets (Springenberg et al., 2014) that replace deterministic spatial pooling functions with strided convolutions. This enables the network to learn its own spatial downsampling and upsampling, benefiting the generator and discriminator.

The second change involves eliminating fully connected layers on top of convolutional features, instead directly connecting the highest convolutional features to the input and output of the generator and discriminator. This strikes a balance between model stability and convergence speed.

The third change is the incorporation of Batch Normalization (Ioffe & Szegedy, 2015) to stabilize learning by normalizing input to each unit. This helps with poor initialization and gradient flow in deeper models, preventing the common failure mode of the generator collapsing all samples to a single point. However, applying Batch Normalization to all layers resulted in sample oscillation and model instability, which was avoided by excluding it from the generator's output layer and the discriminator's input layer.

Activation functions play a role as well. The generator uses ReLU activation, except for the output layer, which uses the Tanh function to quickly saturate and cover the color space of the training distribution. In the discriminator, the leaky rectified activation has shown good performance, especially for higher resolution modeling, in contrast to the maxout activation used in the original GAN paper.

These modifications and advancements in CNN architectures have allowed for stable training and the generation of higher resolution and more realistic images.

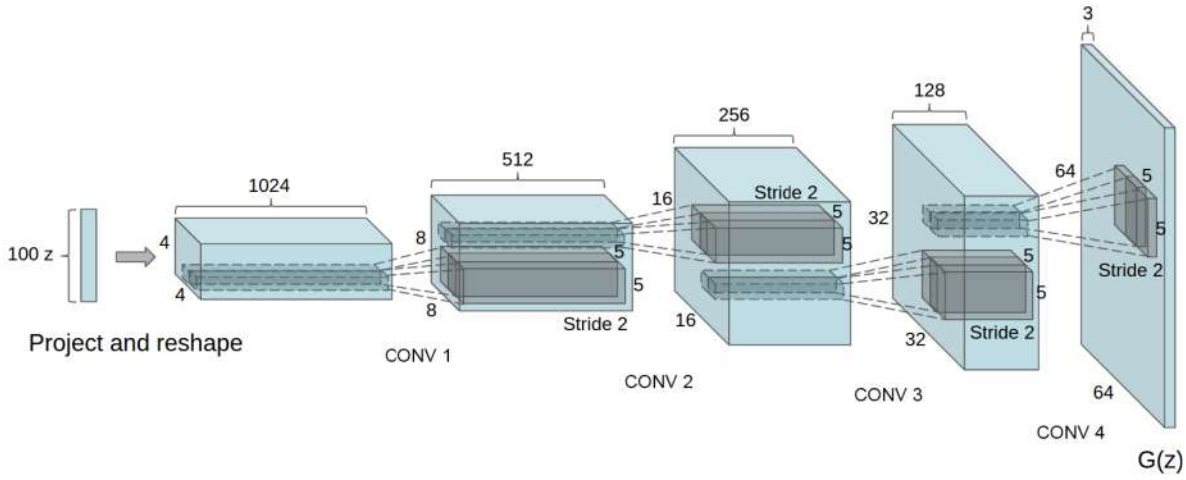

Figure 3: The DCGAN Generator as presented in the LSUN scene modeling paper.

Fig. 3 presents the DCGAN generator, as utilized in LSUN scene modeling, takes a 100-dimensional uniform distribution $\boldsymbol{Z}$ and projects it to a compact spatial representation using convolutional layers with multiple feature maps. Through a series of four fractionally-strided convolutions, this representation is transformed into a $\mathbf{64 \times 64}$ pixel image. Notably, the generator does not employ fully connected or pooling layers. In the LSUN scene modeling paper, this architecture is referred to as the DCGAN generator, and it maps a $\mathbf{100 \times 1}$ noise vector denoted as z to the $\boldsymbol{G(Z)}$ output, which is a $\mathbf{64 \times 64 \times 3}$ image.

This architecture is especially interesting the way the first layer expands the random noise. The network goes from $\mathbf{100 \times 1}$ to $\mathbf{1024 \times 4 \times 4}$. This layer is denoted 'project and reshape'.

We see that following this layer, classical convolutional layers are applied which reshape the network with the $\boldsymbol{(N + P|F)/S + 1}$ equation classically taught with convolutional layers. In the diagram above we can see that the N parameter, (Height/Width), goes from $\mathbf{4}$ to $\mathbf{8}$ to $\mathbf{16}$ to $\mathbf{32}$, it doesn't appear that there is any padding, the kernel filter parameter $\boldsymbol{F}$ is $\mathbf{5 \times 5}$, and the stride is $\mathbf{2}$. You may find this equation to be useful for designing your own convolutional layers for customized output sizes.

We see the network goes from $\mathbf{100 \times 1} \rightarrow \mathbf{1024 \times 4 \times 4} \rightarrow \mathbf{512 \times 8 \times 8} \rightarrow \mathbf{256 \times 16 \times 16} \rightarrow \mathbf{128 \times 32 \times 32} \rightarrow \mathbf{64 \times 64 \times 3}$.

3.2 Cycle Consistent GAN Architecture

CycleGAN is an unsupervised deep learning technique introduced in 2017 for image-to-image translation and style transfer. Unlike traditional approaches, CycleGAN does not require paired training data, making it highly flexible and applicable to various domains. By enforcing cycle consistency, it learns mappings between two different domains, ensuring that an image translated from one domain to another and then back retains its original content. This cycle consistency loss encourages the generators to produce coherent and realistic translations.

The architecture of CycleGAN incorporates convolutional and residual blocks in the generator network. Convolutional layers capture high-level features and encode image content, while residual blocks help refine details and improve image quality. Adversarial training is employed using patch discriminators, which distinguish between real and generated images. This feedback loop improves the quality of the generated images over time, resulting in more realistic and domain-consistent translations.

CycleGAN has found applications in various domains, including style transfer, object transfiguration, and domain adaptation. It has revolutionized image translation by eliminating the need for paired training data and providing a flexible framework for learning mappings between domains. CycleGAN has significantly contributed to advancements in image manipulation, artistic rendering, and computer vision research.

3.2.1 Unpaired Image-to-Image Translation with CycleGAN

Unlike Image-to-Image Translation, The authors of the paper [6], have really proven in one way or another that unpaired Image-to-Image Translation is a cutting-edge deep learning technique that enables the translation of images between two different domains without the need for paired training data. Unlike traditional methods that rely on paired images in both domains, this approach allows for the flexible transformation of images from one domain to another, even when direct correspondences are unknown.

The goal of Unpaired Image-to-Image Translation is to learn a mapping between the two domains that preserves the essential characteristics and semantic content of the images while introducing desired changes in style, appearance, or other visual attributes. This technique leverages advanced generative models, such as generative adversarial networks (GANs) and cycle-consistent adversarial networks (CycleGANs), to effectively capture the underlying distributions of the domains and generate realistic and coherent translations.

By removing the requirement for paired training data, Unpaired Image-to-Image Translation opens up a wide range of possibilities in various applications, including artistic style transfer, domain adaptation, image synthesis, and visual content manipulation. This technique has demonstrated remarkable success in enabling the transfer of styles, textures, and attributes between unrelated image domains, contributing to advancements in computer vision, creative design, and image synthesis research.

3.2.2 Details of CycleGAN architecture

Now that we have understood the intuition behind CycleGAN, let's take a deeper dive into its mechanism for performing unpaired image translation. Using the Apples-to-Oranges Dataset, as proposed by the authors, let's consider a case where we have to translate an image x in Domain A, that is, apples, to an image y in Domain B, that is, Oranges.

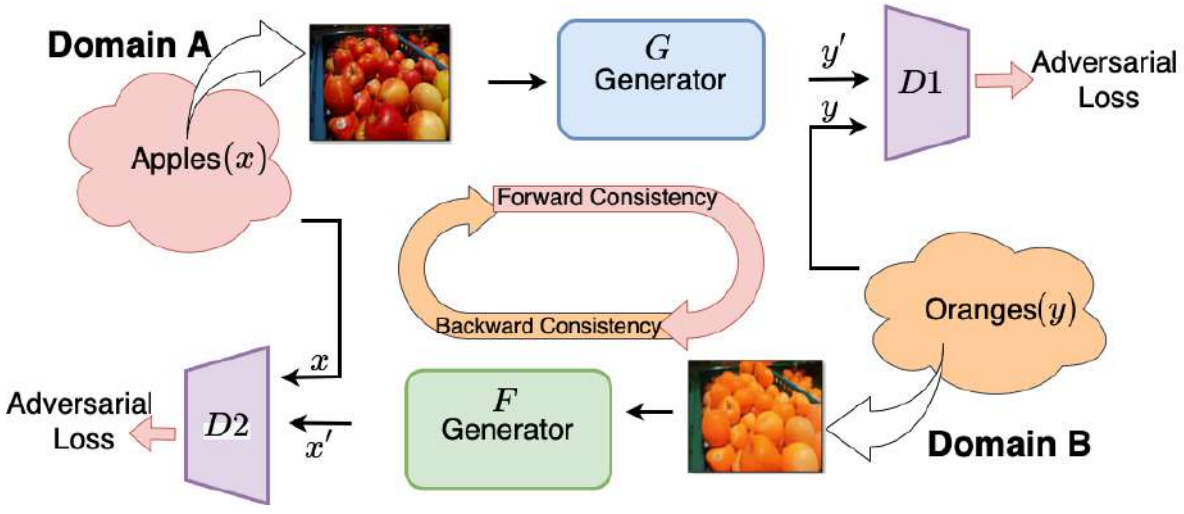

Figure 4: The end-to-end training pipeline of CycleGAN to achieve unpaired Image-to-Image translation (Image proposed by the authors).

First, we take image x from Domain A, which belongs to the distribution of images that depict apples (top). This image is passed through Generator G (as shown), which tries to output an image that belongs to the distribution of images in Domain B.

Discriminator D is an adversary against which differentiates between the samples generated by Generator G (i.e., y') and actual samples from Domain B (i.e., y). The generator is trained against

this adversary using an adversarial training paradigm. This allows the generator to generate images at the output that belong to Domain B's distribution (i.e., oranges).

Similarly, we take an image y from Domain B, which belongs to the distribution of images that depict oranges (bottom). This image is passed through a Generator F (as shown), which tries to output an image that belongs to the distribution of images in Domain A.

Discriminator D is an adversary against which differentiates between the samples generated by Generator F (i.e., x') and actual samples from Domain A (i.e., x). The generator is trained against this adversary using an adversarial training paradigm. This allows the generator to generate images at the output that belong to the distribution of Domain A (i.e., apples).

Finally, we notice that in addition to the two adversarial losses, we also have the forward and backward cyclic consistency losses. This ensures that:

- For each image x from Domain A, the image translation cycle should be able to bring x back to the original image.
- For each image y from Domain B, the image translation cycle should be able to bring y back to the original image.

4 Datasets

MVTec AD is a dataset for benchmarking anomaly detection methods with a focus on industrial inspection. It contains over 5000 high-resolution images divided into fifteen different object and texture categories. Each category comprises a set of defect-free training images and a test set of images with various kinds of defects as well as images without defects.

Pixel-precise annotations of all anomalies are also provided. More information can be in our paper [1] and its extended version [2].

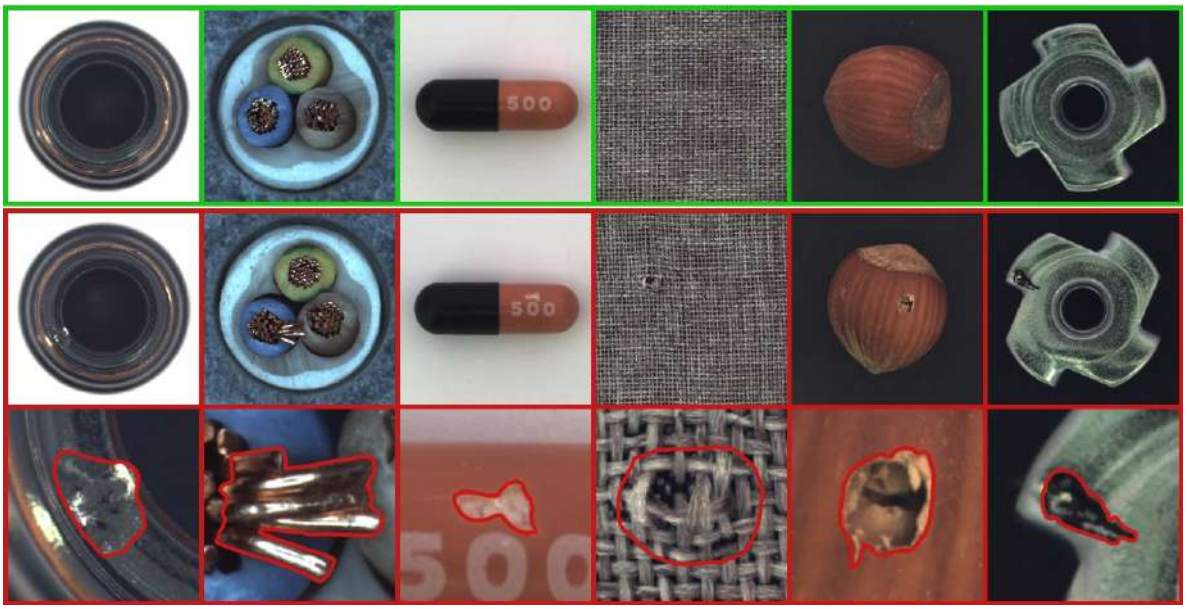

Figure 5: MVTec AD example images.

4.1 Dataset I

Cable: The cable class in the MVTec Anomaly Detection Dataset encompasses different types of cables used in various industries, such as power cables, data cables, or wiring harnesses. Anomalies in this class may involve issues like cuts, fraying, corrosion, or disconnections. Detecting anomalies in cables is vital for guaranteeing reliable electrical connections, preventing accidents or malfunctions, and maintaining optimal performance in different applications.

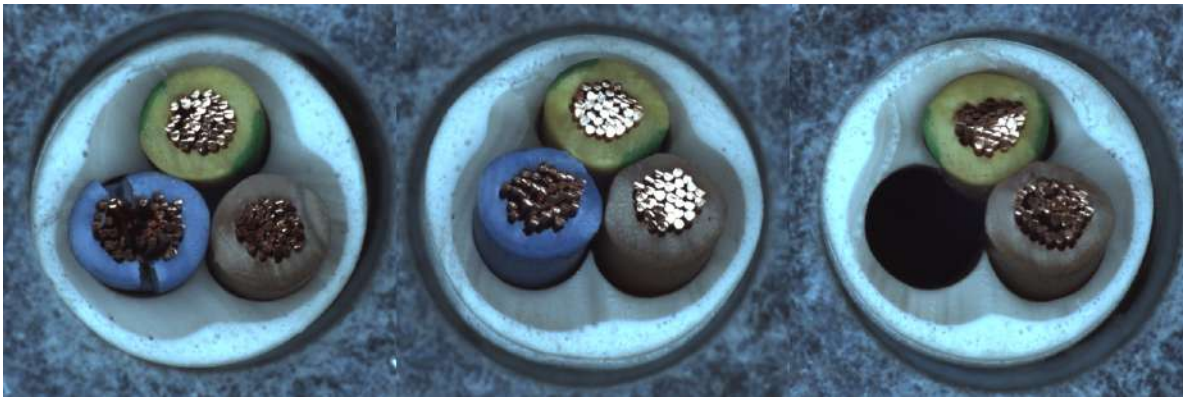

Figure 6: Anomaly Detection in Cables.

4.2 Dataset II

Capsule: The capsule class in the MVTec Anomaly Detection Dataset represents small, encapsulated objects that are commonly found in pharmaceutical, food, or cosmetic industries. These capsules are typically filled with substances such as medication, nutrients, or powders. Anomalies in this class may include deformations, cracks, leaks, or incomplete encapsulation. Detecting anomalies in capsules is crucial for ensuring product quality, preventing contamination, and maintaining the desired properties of the encapsulated substances.

Figure 7: Anomaly Detection in Capsules.

4.3 Dataset III

Metal Nut: The metal nut class in the MVTec Anomaly Detection Dataset comprises different types of nuts, such as hexagonal or round-shaped, commonly used in mechanical assemblies and fastening applications. Anomalies in this class may include deformations, cracks, missing threads, or improper dimensions. Detecting anomalies in metal nuts is important for ensuring the reliability and stability of mechanical structures, preventing loosening or failures, and maintaining the desired functionality in various industries, including automotive, aerospace, or machinery.

4.4 Dataset IV

Transistor: The transistor class in the MVTec Anomaly Detection Dataset represents electronic components used in various devices, including computers, smartphones, and electrical circuits. Transistors are vital for controlling the flow of electric currents within these devices. Anomalies in this class may involve issues such as cracks, broken connections, excessive heat, or incorrect positioning. Detecting

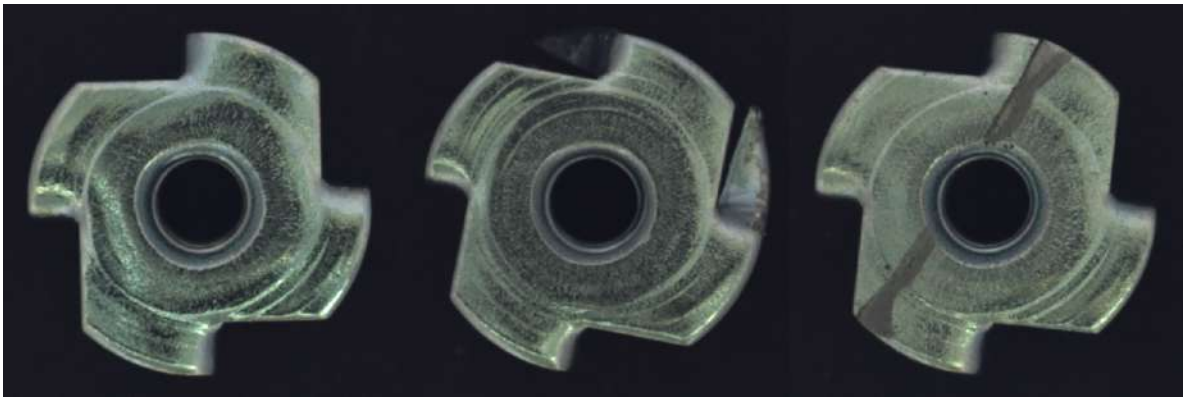

Figure 8: Anomaly Detection in Metal Nuts.

anomalies in transistors is critical for ensuring the proper functioning of electronic devices, preventing malfunctions, and maintaining optimal performance.

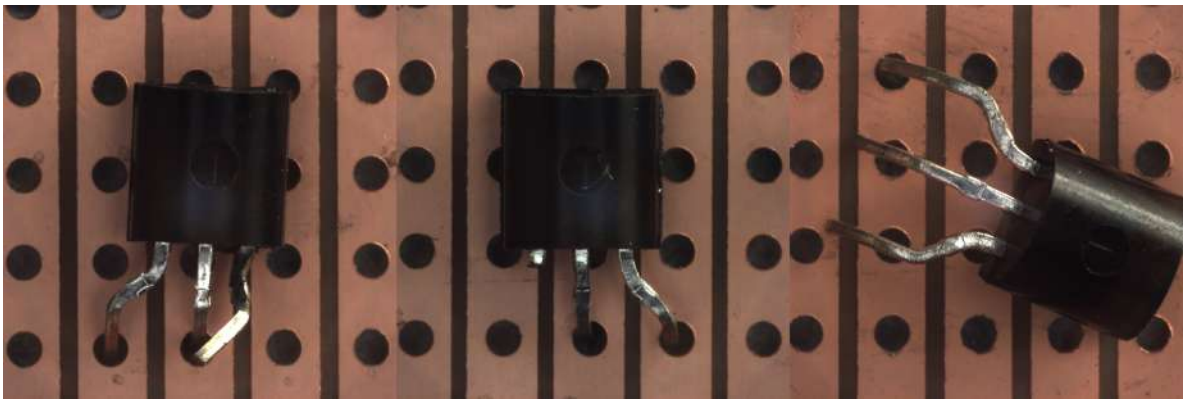

Figure 9: Anomaly Detection in Transistors.

5 Data augmentation

5.1 DCGAN

We trained multiple instances of DCGAN outlined below. The architecture of DCGAN was kept unchanged for each instance and learning rate of 0.0002 was used for the discriminator and generator, respectively. Experimenting with the size of the Gaussian noise vector z showed 100 to be the optimal size. We trained our DCGAN for 20000+ epochs on Kaggle using GPU P100 - 16 GB with a batch size of 64 for every instance of the used Datasets. For dataset I, DCGAN was trained on 234 Cable images and tested on 140 images. For dataset II, DCGAN was trained on 229 Capsule images and tested on 122 images. For dataset III, DCGAN was trained on 23o Metal Nut images and tested on 105 images. For dataset IV, DCGAN was trained on 223 Transistor images and tested on 90 images. After successful training of the DCGAN, the generator has learned the distribution of the images of the training class.

To generate new data, for each input image to DCGAN, a random noise vector was initiated and 100 new images were generated from the generator (The 100 images generated was fixed to evaluate the models created equally). Fig. (10, 11, 12, 13) Shows the generator's output at early, mid and later stages (from left to right respectively) of the training on Datasets.

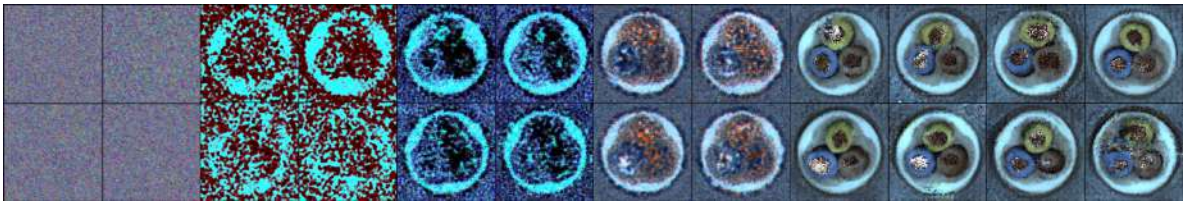

Figure 10: Training images of Dataset I (Cables) around 2×10^4 epochs.

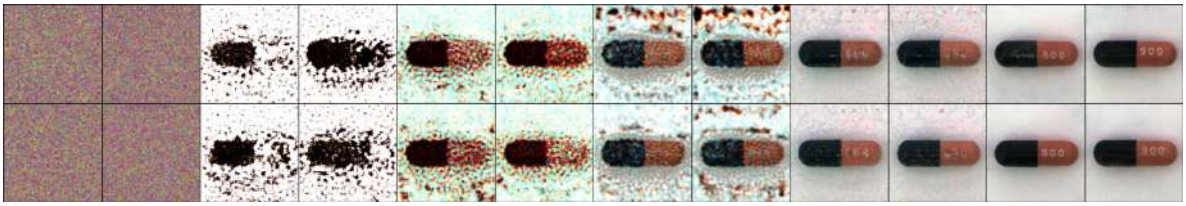

Figure 11: Training images of Dataset II (Capsules) around 3×10^4 epochs.

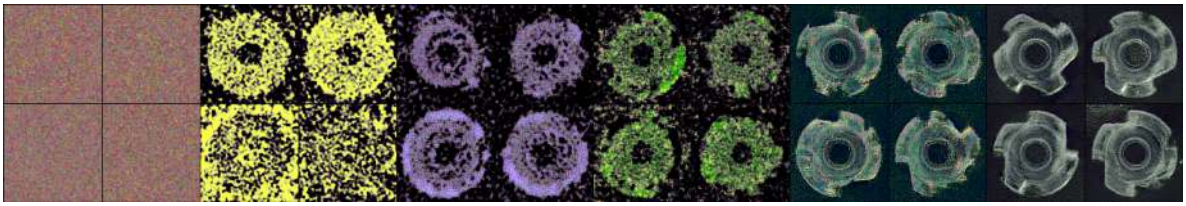

Figure 12: Training images of Dataset III (Metal Nuts) around 4×10^4 epochs.

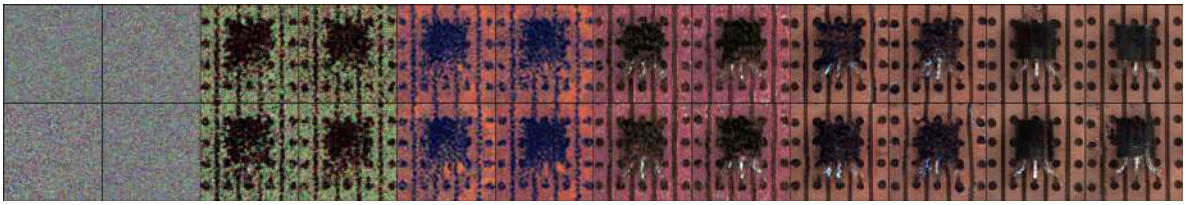

Figure 13: Training images of Dataset IV (Transistors) around 10^4 epochs.

5.2 CycleGAN

We trained multiple instances of CycleGAN outlined below. The architecture of CycleGAN was kept unchanged for each instance and learning rate of 0.0002 was used for the pair of the discriminator and generator, respectively. We trained our CycleGAN for 800+ epochs on Kaggle using GPU P100 - 16 GB with a batch size of 32 for every instance of the used Datasets. For dataset I, CycleGAN was trained on 234 Cable images and tested on 140 images. For dataset II, CycleGAN was trained on 229 Capsule images and tested on 122 images. For dataset III, CycleGAN was trained on 23o Metal Nut images and tested on 105 images. For dataset IV, CycleGAN was trained on 223 Transistor images and tested on 90 images. After successful training of the CycleGAN, the generator has learned the distribution of the images of the training class.

To generate new data, for each input image to CycleGAN, a random noise vector was initiated, two images were choosen from the the dataset in order to trnasfer styles between them and 200 new images were generated from the generators (The 200 images generated was fixed to evaluate the models created equally). Fig. (14, 15, 16, 17) show the generators's output at early, mid and later stages (from left to right respectively) of the training on Datasets.

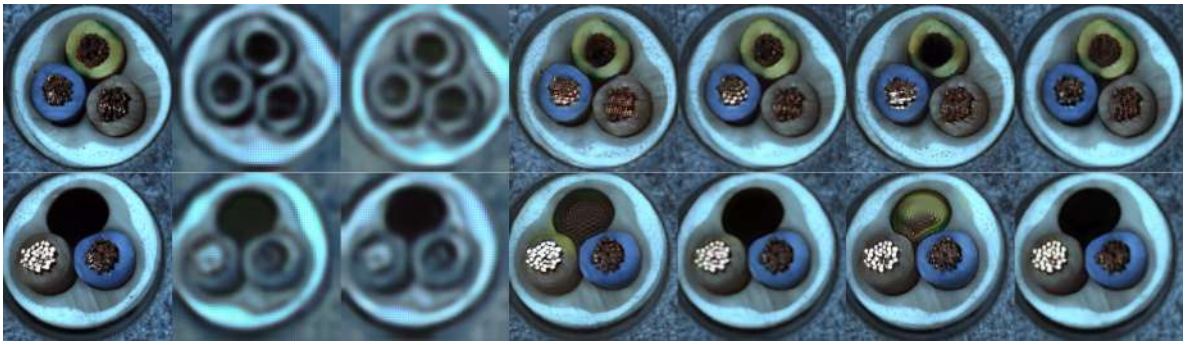

Figure 14: Training images of Dataset I (Cables) around 899 epochs.

Figure 15: Training images of Dataset II (Capsules) around 805 epochs.

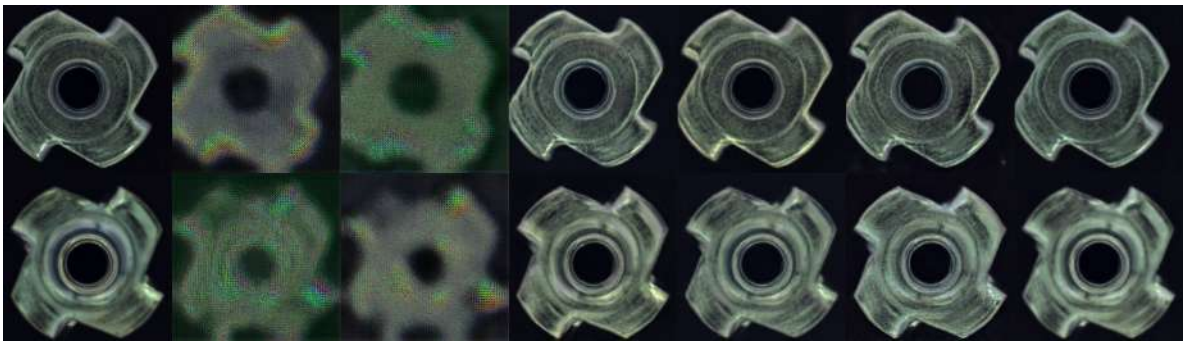

Figure 16: Training images of Dataset III (Metal Nuts) around 805 epochs.

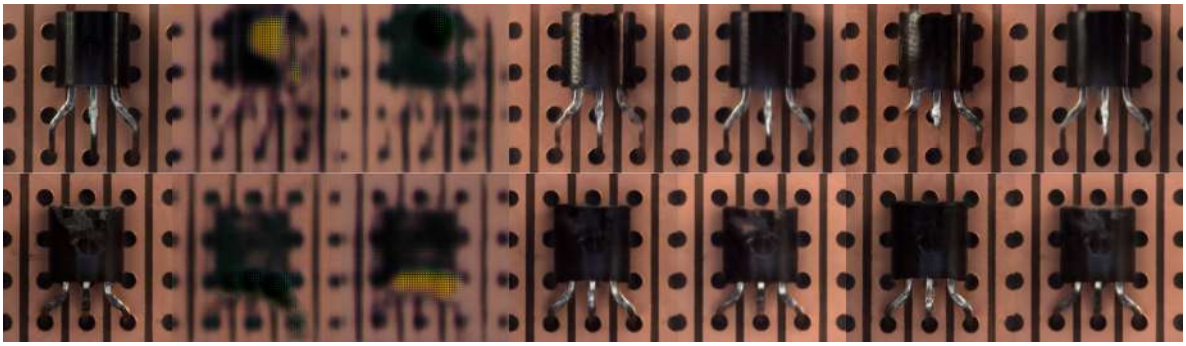

Figure 17: Training images of Dataset IV (Transistors) around 800 epochs.

6 Results

In order to evaluate the generations of our GANs we augmented each dataset by 100 images and we implemented a vanilla Convolutional Neural Network (CNN) architecture for classification, I utilized the four datasets and evaluated the performance using metrics such as Specificity, Sensitivity, and Accuracy. Each dataset of the four datasets used for training were modified as follow:

1. Non augmented dataset.
2. Simple augmentation dataset.
3. DCGAN augmented dataset.
4. CycleGAN augmented dataset.

In the first scenario, I trained the GAN using the original dataset with no augmentation. This means that the dataset remained unchanged, and the GAN learned directly from the original images. I evaluated the performance of the CNN for classification using metrics such as Specificity, Sensitivity, and Accuracy to assess its ability to classify those images.

No Augmentation	**Sensitivity**	**Specificity**	**Accuracy**
Dataset I	0.965	0.109	0.464
Dataset II	1.0	0.0	0.188
Dataset III	1.0	0.0	0.209
Dataset IV	1.0	0.2	0.733

Table 1: Sensitivity, Specificity and Accuracy metrics with No Augmentation.

In the second scenario, I introduced simple augmentation techniques to the dataset. This involved applying basic transformations such as rotation, scaling, and flipping to increase the variability of the training data. The CNN was trained on this augmented dataset, and its performance was evaluated using the same metrics as before.

Simple Augmentation	**Sensitivity**	**Specificity**	**Accuracy**
Dataset I	1.0	0.244	0.557
Dataset II	1.0	0.0	0.188
Dataset III	1.0	0.0	0.209
Dataset IV	1.0	0.133	0.711

Table 2: Sensitivity, Specificity and Accuracy for dataset II.

For the third scenario, I employed a DCGAN architecture, which is a variant of the CNN specifically designed for generating images. The GAN was trained on a dataset specifically prepared for DCGAN, which may include additional pre-processing steps. The generated images were then evaluated using the specified metrics below.

DCGAN	**Sensitivity**	**Specificity**	**Accuracy**
Dataset I	1.0	0.0	0.758
Dataset II	1.0	0.0	0.692
Dataset III	1.0	0.0	0.727
Dataset IV	1.0	0.0	0.896

Table 3: Sensitivity, Specificity and Accuracy for dataset III.

Lastly, in the fourth scenario, I utilized the CycleGAN architecture. Unlike the previous scenarios, the CycleGAN model aimed to learn a mapping between two different image domains in case of our dataset is to differentiate between *Good* and *Bad* parts. This GAN was trained on a dataset containing paired images from the source and target domains, and the generated images were evaluated using the specified metrics below.

CycleGAN	Sensitivity	Specificity	Accuracy
Dataset I	1.0	0.354	0.621
Dataset II	1.0	0.80	0.892
Dataset III	1.0	0.878	0.935
Dataset IV	1.0	0.930	0.966

Table 4: Sensitivity, Specificity and Accuracy for dataset IV.

Throughout the training process, I focused on assessing the Specificity, Sensitivity, and Accuracy of the GAN models to gauge their ability to generate realistic images and capture the characteristics of the target domains. These metrics provided insights into the performance of the GAN models in terms of correctly identifying the desired features, minimizing false positives, and accurately reproducing the images from the target domain. By comparing the results across the different datasets and GAN architectures, I gained valuable insights into the effectiveness of each approach and identified the most suitable method for generating high-quality images.

After evaluating the metrics, I summarized the Area Under the Curve (AUC) and p-value for each dataset in a Table. 5 . The AUC provides a measure of the overall performance of the GAN models, indicating how well they can discriminate between real and generated images. A higher AUC signifies better performance. The p-value, on the other hand, helps determine the statistical significance of the differences observed between the datasets. By comparing the AUC values and p-values across the different datasets, I was able to identify the dataset and GAN architecture that yielded the best results. This analysis allowed me to make informed decisions regarding the effectiveness of the GAN models and the impact of augmentation and different GAN architectures on their performance.

Dataset	No augmentation	Simple augmentation	DCGAN	CycleGAN
Dataset I	$0.537/2 \times 10^{-22}$	$0.622/4.5 \times 10^{-16}$	$0.5/1.6 \times 10^{-23}$	$0.677/2 \times 10^{-11}$
Dataset II	$0.5/2 \times 10^{-62}$	$0.5/3 \times 10^{-62}$	$0.5/8.3 \times 10^{-30}$	$0.900\ 3.8 \times 10^{-6}$
Dataset III	$0.5/9 \times 10^{-50}$	$0.5/9 \times 10^{-50}$	$0.5/1.9 \times 10^{-24}$	$0.939\ 5.5 \times 10^{-3}$
Dataset IV	$0.6/2 \times 5^{-6}$	$0.566/3.44 \times 10^{-7}$	$0.5/1.3 \times 10^{-8}$	0.965 0.154

Table 5: AUC and p-value for datasets I and II.

7 Discussion

This article aims to explore the effectiveness of data augmentation techniques and different GAN architectures, namely DCGAN and CycleGAN, in generating realistic images for classification tasks. We evaluated the performance of these models on four different datasets and compared the results to assess their capabilities.

In the first scenario, we trained the CNN on the original dataset with no augmentation. The performance of the CNN on this dataset was generally poor, with low values for sensitivity, specificity, and accuracy. This suggests that the CNN struggled to capture the underlying patterns and features of the images, leading to inaccurate classification results. The low specificity indicates a high rate of false positives, while the low sensitivity indicates a high rate of false negatives. These results highlight the limitations of training a CNN on a small, unaltered dataset.

To address the limitations of the original dataset, we introduced simple augmentation techniques in the second scenario. This involved applying basic transformations such as rotation, scaling, and flipping to increase the variability of the training data. The performance of the CNN on the augmented dataset showed improvement compared to the original dataset, particularly in terms of sensitivity and accuracy. This suggests that data augmentation helped the CNN better generalize the underlying patterns and features of the images, resulting in improved classification performance. However, the specificity remained low, indicating a continued high rate of false positives.

In the third scenario, we employed the DCGAN architecture to generate augmented data. The DCGAN was trained on a specific dataset prepared for DCGAN, and the generated images were evaluated using the CNN. The results showed significant improvement in the performance metrics compared to the original and simply augmented datasets. The sensitivity remained high, indicating a low rate of

false negatives, while the specificity improved compared to the simply augmented dataset. The accuracy also improved substantially, suggesting that the generated images by the DCGAN captured the essential features of the training class and contributed to better classification results. These findings demonstrate the effectiveness of DCGAN in generating realistic images for classification tasks.

Lastly, in the fourth scenario, we utilized the CycleGAN architecture, which aimed to learn a mapping between two different image domains. The CycleGAN was trained on paired images from the source and target domains, and the generated images were evaluated using the CNN. The results showed the highest performance metrics across all datasets and GAN architectures. The sensitivity, specificity, and accuracy values were significantly improved compared to the other scenarios, indicating the superior performance of CycleGAN-generated images. The high specificity suggests a reduced rate of false positives, while the high sensitivity indicates a reduced rate of false negatives. These results demonstrate that CycleGAN successfully captured the distinctive features of the target domain and generated high-quality images for classification.

Comparing the performance of the different GAN architectures, CycleGAN outperformed DCGAN in terms of overall image quality and classification performance. This can be attributed to the specific design of CycleGAN for image domain translation, which allowed it to capture and transfer the style and characteristics of the target domain effectively. DCGAN, on the other hand, generated images that exhibited some level of diversity but may have lacked the fine details and specific features of the target domain.

In conclusion, this article's case study highlights the importance of data augmentation and the effectiveness of GAN architectures in generating realistic images for classification tasks. The results demonstrate that simple augmentation techniques can improve classification performance, but the use of specialized GAN architectures such as DCGAN and CycleGAN can further enhance image quality and classification accuracy. The generated images by CycleGAN exhibited the highest performance metrics, indicating its superiority in capturing the characteristics of the target domain. These findings have practical implications in various domains where data augmentation and image generation are crucial for improving classification tasks and advancing the capabilities of deep learning models. For advanced research we could really focus on exploring other GAN architectures and advanced augmentation techniques to further improve image generation and classification performance.

8 Conclusion

We've investigated so far the effectiveness of data augmentation techniques and two different GAN architectures, DCGAN and CycleGAN, in generating realistic images for classification tasks. Our findings demonstrate the importance of augmenting training data and the potential of GANs in improving image quality and classification performance.

Overall, this article emphasizes the importance of data augmentation in enhancing classification tasks. Augmenting training data improves the CNN's ability to generalize and recognize patterns. Mainly, that's achieved through generating high-quality images that contribute to superior classification performance.

These findings have practical implications for various domains where accurate classification is crucial. By leveraging data augmentation and advanced GAN techniques, We can enhance the capabilities of our models to achieve more reliable and accurate results.

In conclusion, while this study focused on data augmentation and GAN architectures for image classification, there are numerous promising avenues for future research. By exploring hybrid approaches, novel GAN architectures, transfer learning, evaluating on different datasets, analyzing robustness, and focusing on real-time implementation, we can further enhance the state-of-the-art in this field. These alternative directions, such as investigating other GAN architectures and advanced augmentation techniques, can potentially yield even better results. Additionally, evaluating the generalizability of these findings across different datasets and classification tasks would provide valuable insights.

Furthermore, combining traditional data augmentation techniques with GAN-generated images in hybrid approaches offers the potential for a more diverse and comprehensive training dataset. Exploring transfer learning with GANs can enhance the quality of generated images and improve overall classification performance. Investigating novel GAN architectures, evaluating on different datasets, analyzing robustness against adversarial attacks, and focusing on real-time implementation are all valuable areas of future research.

By embracing these alternative plans, we can push the boundaries of image classification, contribute to advancements in machine learning and computer vision, and ultimately achieve further improvements in classification accuracy. Moreover, expanded applications of image recognition technology and a deeper understanding of the power and potential of data augmentation and GAN architectures can be achieved through continued exploration and innovation.

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