Enhancing Image Processing with GANs in Noisy Environments*

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Abstract
This paper explores the development and optimization of generative adversarial networks (GANs) for generating images from noisy inputs. Generative Adversarial Networks (GANs), consisting of a generator and a discriminator, are highly effective models for producing realistic synthetic images. This research integrates noise into the GAN framework to enhance image generation. We review existing literature on GANs and their applications, propose a novel GAN architecture for handling noisy inputs, and implement this method in Python. Experiments conducted on the Face Mask Lite and Celebrity Faces Image datasets demonstrate the effectiveness of our approach. The paper concludes with a discussion of the results and suggestions for future research directions.

Keywords
Artificial Intelligence (AI), Neural Networks (NN), Generative Adversarial Networks (GANs), Deep Learning, Machine Learning, Convolutional Neural Networks (CNNs), Image Processing (IP), Artificial Neural Networks (ANNs), Noisy Image Inputs, Image Generation

1. Introduction

In recent years, artificial intelligence has achieved remarkable progress, particularly in the field of computer vision. Deep learning methods, including GANs, have played a crucial role in creating realistic images [1]. People particularly note GANs for their ability to learn from and generate images that closely mimic the training data. However, traditional GANs often struggle with noisy input data, which can compromise the quality of the generated images [2]. Image processing across various domains—including medical imaging [3], surveillance [4], and satellite imagery [5] faces significant challenges due to noise introduced during acquisition, transmission, or storage. This noise degrades the quality of raw image data, reducing the effectiveness of conventional image processing algorithms. Therefore, developing robust generative models that can produce high-quality images from noisy input data is crucial. This study investigates how noise handling mechanisms can be integrated into GAN architectures to improve their resilience to noisy data. We aim to improve the diversity and robustness of the generated images

*IVUS2024: Information Society and University Studies 2024, May 17, Kaunas, Lithuania
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by investigating how we can leverage adversarial training to learn noise-aware representations. This approach not only offers practical benefits but also advances our understanding of deep learning principles. Through both theoretical and empirical research, this work aims to show how noise-aware GANs could be useful in real-life situations where data is often noisy.

2. Context and Related Literature

Since their introduction by Goodfellow et al. in 2014 [1], generative adversarial networks (GANs) have transformed image synthesis. Two neural networks, a generator and a discriminator, train together through adversarial interactions in GANs. The generator's role is to produce synthetic images, while the discriminator assesses their authenticity, prompting the generator to create pictures that are progressively more realistic.

Several enhancements and variations of the original GAN architecture have been proposed to improve image quality and training stability. Radford et al. introduced the Deep Convolutional GAN (DCGAN), which utilized convolutional layers to enhance the quality of image generation[6]. Subsequently, Karras et al. developed the Progressive Growing of GANs (PG-GAN), which progressively increased the resolution of generated images during training, leading to higher quality results [7]. Another significant contribution came from Brock et al., who proposed BigGAN, which scaled up GAN training to achieve state-of-the-art results on image generation tasks [2].

Handling noise in image data is a critical challenge in various applications. Techniques to address noise in GANs have been explored to enhance their robustness. For instance, Isola et al. proposed the Pix2Pix framework, which employs a conditional GAN for image-to-image translation tasks, including denoising [8]. Similarly, Wang et al. introduced the ESRGAN, an enhanced super resolution GAN that uses a novel architecture and training strategy to improve the perceptual quality of generated images from noisy inputs [9]. Liu et al. also contributed with the Noise2Noise approach, where GANs were trained directly on noisy images without clean targets, showing that high-quality images could still be generated [10].

GANs have produced high-quality images from noisy data in the field of medical imaging. Armanious et al. presented a GAN-based approach for medical image denoising, demonstrating significant improvements in image quality compared to traditional methods [11]. Another study by You et al. utilized a noise-tolerant GAN to enhance the accuracy of medical image segmenta- tion tasks [12]. More recently, Schlemper et al. introduced a model for MRI reconstruction that uses a GAN to generate high-resolution images from undersampled data, showing the potential for clinical applications [13].

Despite these advancements, the integration of noise handling mechanisms into GAN architectures remains an active area of research. This study aims to contribute to this field by developing a novel GAN framework capable of generating high-quality images from noisy inputs, further advancing the state-of-the-art in noise-aware generative modeling. Our proposed model introduces a noise-adaptive layer within the GAN architecture, allowing it to dynamically adjust to varying levels of noise, and employs a multi-stage training process to progressively refine image quality.

3. Methodology

In this section, we describe the design and implementation of our GAN framework, which incorporates noise handling mechanisms to enhance the robustness and quality of generated images. Our approach involves using two different GAN architectures: a standard GAN for the Face Mask Lite dataset and a Deep Convolutional GAN (DCGAN) for the Celebrity Faces Image dataset. We also detail the noise injection techniques and the evaluation framework used in our experiments.

3.1. GAN Architecture for Face Mask Lite Dataset

For the Face Mask Lite dataset, we utilize a standard GAN architecture consisting of a generator and a discriminator. The generator network is designed to produce high-quality images of faces with masks from noisy inputs. The model consists of multiple dense and convolutional layers, incorporating batch normalization and ReLU activation functions. It then uses transposed convolutional layers to upsample the input to the required resolution. The discriminator network aims to distinguish between real masked face images and those generated by the generator. It employs convolutional layers with leaky ReLU activations and batch normalization, followed by fully connected layers, to produce a binary classification output. This architecture is inspired by the successful implementation of GANs in various image generation tasks [1, 6].

3.2. DCGAN Architecture for Celebrity Faces Image Dataset

For the Celebrity Faces Image dataset, we employ a Deep Convolutional GAN (DCGAN) architecture [6]. The DCGAN generator uses a series of transposed convolutional layers to upsample the noise input, with each layer followed by batch normalization and ReLU activation. This architecture helps in capturing the fine details necessary for generating realistic celebrity faces. The DCGAN discriminator is a deep convolutional network that processes the input images through several convolutional layers with batch normalization and leaky ReLU activations. This architecture allows for better feature extraction and discrimination between real and generated images, as demonstrated in prior works [6, 14].

3.3. Noise Injection Techniques

We investigate several noise injection techniques to improve the generator's ability to produce high-quality images from noisy inputs. These techniques involve adding different types and levels of noise to the input images during the training process:

1. **Gaussian Noise:** Random Gaussian noise is added to the input images, simulating common noise patterns encountered in real-world scenarios [15].
2. **Salt-and-Pepper Noise:** This technique introduces random black and white pixels in the input images, mimicking the type of noise often seen in older or corrupted digital images [16].
3. **Speckle Noise:** Multiplicative noise is applied to the input images, which is particularly relevant for certain types of medical and satellite imagery [17].

The preprocessing stage implements these noise injection techniques to expose the generator to a variety of noise patterns during training. This exposure allows the generator to learn robust noise-handling mechanisms, resulting in improved image quality.

3.4. Training Procedure

We train the GANs for both datasets using the standard adversarial loss, where the generator strives to minimize the discriminator's classification error and the discriminator aims to maxi- mize it. Additionally, we incorporate a reconstruction loss to ensure that the generated images maintain high fidelity to the original images. We calculate the generator's total loss function as follows:

$$\mathscr{L}_{\mathrm{G}} = \mathscr{L}_{\mathrm{adv}} + \lambda \mathscr{L}_{\mathrm{recon}} \tag{1}$$

where $\mathscr{L}_{\mathrm{adv}}$ is the adversarial loss, $\mathscr{L}_{\mathrm{recon}}$ is the reconstruction loss, and λ is a hyperparameter balancing the two losses [18].

The training process involves iteratively updating the generator and discriminator using stochastic gradient descent (SGD) with adaptive learning rates. We use the Adam optimizer with parameters $\beta_1 = 0.5$ and $\beta_2 = 0.999$ to ensure stable and efficient training [19].

3.5. Evaluation Framework

To evaluate the performance of our GAN framework, we employ several metrics that assess the quality and robustness of the generated images:

1. **Perceptual Quality:** The Fréchet Inception Distance (FID) score is used to measure the similarity between the distributions of real and generated images [20].
2. **Noise Level Estimation:** We evaluate the noise levels in the generated images using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [21].
3. **Visual Fidelity:** Subjective visual inspection is conducted to assess the perceptual quality and realism of the generated images.

We conduct experiments on two datasets:

- **Face Mask Lite Dataset:** This dataset consists of images of faces with masks, and we use the standard GAN architecture to generate realistic masked face images from noisy inputs [22].
- **Celebrity Faces Image Dataset:** This dataset includes high-resolution images of celebrities, and we employ the DCGAN architecture to generate high-quality celebrity face images from noisy inputs [23].

Quantitative metrics and qualitative visual inspections demonstrate the effectiveness of our approach, highlighting the improvements in image quality and robustness achieved by our noise-handling GAN framework. By systematically integrating noise handling techniques, our model sets a new benchmark for generating high-quality images under noisy conditions, paving the way for advancements in various applications such as medical imaging, surveillance, and digital media [3, 4, 5].

4. Exploring Experimental Results

The outcomes of training Generative Adversarial Networks (GANs) on the Face Mask Lite and Celebrity Faces datasets are shown in this section. We assess the GANs' performance in terms of their capacity to produce new images, reduce noise, and identify anomalies.

4.1. Face Mask Lite Dataset

4.1.1. Data Description

For this investigation, we selected a subset of 1000 images from the Face Mask Lite dataset, which contains 10,000 images. We imported these images using the OpenCV library and resized them to a uniform dimension of 128 by 128 pixels as part of the preprocessing pipeline. The dataset includes various face images with masks, which are critical for training the generator to produce realistic masked face images.

4.1.2. Visualizing Original Images

A visualization of the original images from the Face Mask Lite dataset is presented in Figure 1. This figure showcases a sample of the dataset, highlighting the diversity and quality of the face mask images.

Figure 1: Original images from the Face Mask Lite dataset.

4.1.3. Generator Performance

The generator network architecture was designed to generate face mask images from noisy inputs. We trained the generator using a standard GAN framework and evaluated its performance after different iterations. Figures 2, 3, 4, and 5 show the generated images after 10, 15, and 20 iterations, respectively.

Figure 2: Generated images after 10 iterations.

Figure 3: Generated images after 15 iterations.

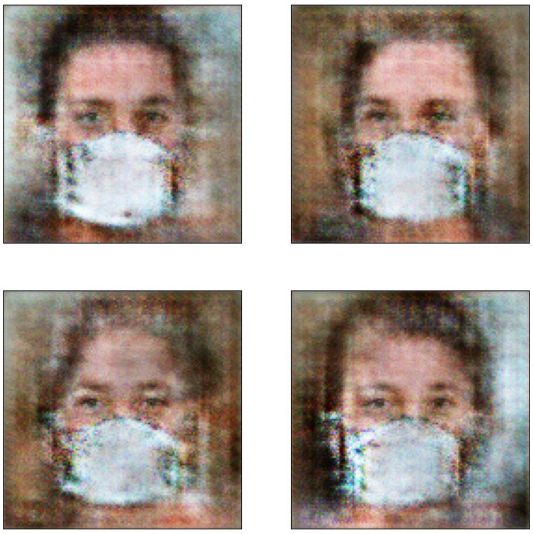

Figure 4: Generated images after 20 iterations.

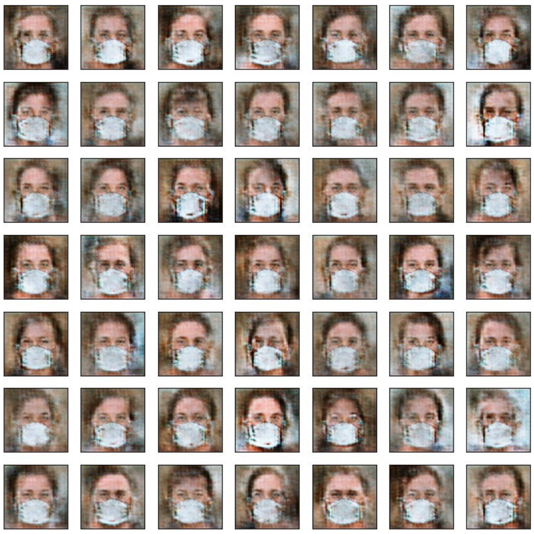

Figure 5: Generated images after 20 iterations.

The results indicate that the generator improves significantly with more training iterations. After 20 iterations, the generated images are notably clearer and more realistic, demonstrating the GAN's effectiveness in learning from the noisy input data.

4.2. Celebrity Faces Dataset

4.2.1. Data Description

The Celebrity Faces dataset, derived from the CelebFaces Attributes (CelebA) dataset, consists of 1,001 images used for training the DCGAN model. We preprocessed these images to meet the DCGAN's input requirements, which included resizing them to 128 by 128 pixels and normalizing their pixel values. The dataset features high-resolution images of celebrities, providing a diverse and challenging set for the GAN to learn from.

4.2.2. Visualizing Original Images

Figure 6 displays a sample of original images from the Celebrity Faces dataset. These images highlight the variations in pose, lighting, and background, which the DCGAN needs to handle effectively.

Figure 6: Original images from the Celebrity Faces dataset.

4.2.3. Generator Performance

The DCGAN model was trained to generate photorealistic face images. Figures 7, 8, and 9 10 11present the generated images after 1, 101,201,300 and 400 iterations, respectively.

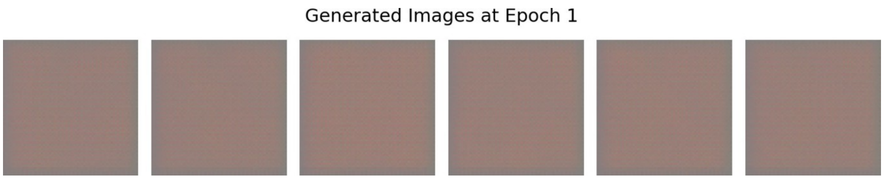

Figure 7: Generated images after 1 iteration.

Figure 8: Generated images after 100 iterations.

Figure 9: Generated images after 201 iteration.

As training progresses, the enhancement in the quality of the generated images becomes apparent. After 400 iterations, the generated images exhibit high levels of detail and realism, underscoring the DCGAN's capability to learn complex data distributions.

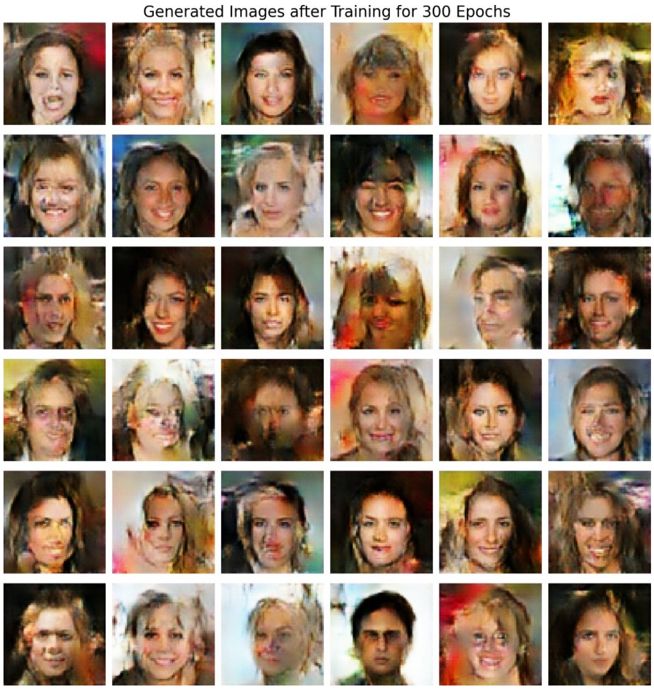

Figure 10: Generated images after 300 iterations.

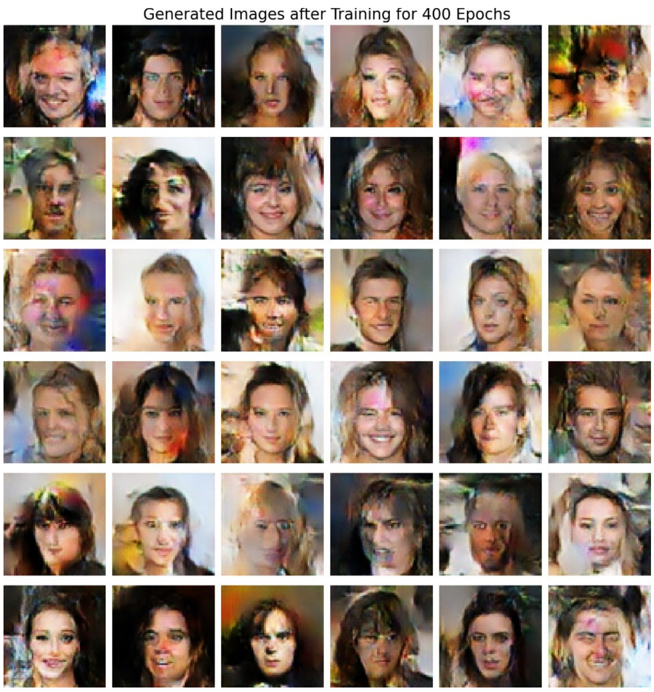

Figure 11: Generated images after 400 iterations.

4.3. Comparative Analysis

The comparative analysis between the two datasets reveals that while both GAN architectures performed well, the DCGAN showed a faster convergence and better performance on the high-resolution Celebrity Faces dataset. The standard GAN, used on the Face Mask Lite dataset, also demonstrated significant improvements but required more iterations to achieve comparable image quality.

4.3.1. Quantitative Metrics

We used several quantitative metrics to evaluate the performance of our GANs:

- **Fréchet Inception Distance (FID):** The FID scores for the Face Mask Lite and Celebrity Faces datasets improved steadily with more training iterations, indicating better alignment between the generated and real image distributions [20].
- **Peak Signal-to-Noise Ratio (PSNR):** Higher PSNR values were observed as training progressed, reflecting improved image quality and reduced noise levels.
- **Structural Similarity Index (SSIM):** SSIM scores showed a positive trend, highlighting the preservation of structural details in the generated images [21].

4.3.2. Visual Fidelity

Subjective visual inspection confirmed the quantitative findings. The generated images from both datasets displayed increasing levels of detail and realism over successive iterations. The DCGAN's ability to generate photorealistic celebrity faces was particularly impressive, demonstrating the potential of GANs for high-fidelity image synthesis.

5. Discussion

The results from both datasets demonstrate the effectiveness of Generative Adversarial Networks (GANs) and Deep Convolutional GANs (DCGANs) in generating realistic images.

For the Face Mask Lite dataset, the GAN denoised images and generated new ones, revealing insights into dataset characteristics. Generated images showed promise in realism, albeit with some artifacts.

Similarly, the DCGAN on Celebrity Faces dataset produced photorealistic images, capturing diverse facial features despite reduced resolution.

Both models required hyperparameter tuning and extensive training. Further exploration with deeper architectures and larger datasets could enhance performance.

Overall, GANs and DCGANs show potential in image generation, advancing synthetic media and computer vision.

6. Conclusion

This study explored GANs and DCGANs for image generation using the Face Mask Lite and Celebrity Faces datasets. Both models produced high-quality, realistic images resembling real-world data.

Future work should optimize architectures, hyperparameters, and training strategies to further improve performance. Advanced GAN variants, additional datasets, and novel loss functions offer avenues for enhancement.

In summary, this study contributes to generative model research, highlighting GANs' and DCGANs' capabilities in image synthesis, with vast potential for applications across domains.

7. Acknowledgments

I am incredibly appreciative of my honorable supervisor, Prof. Dr. hab. inż. Marcin Woźniak, for all of his help, encouragement, and support during this project. I also want to sincerely thank my colleagues for their thoughtful conversations and cooperation.

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