GAN for Synthetic Image Generation

PROJECT PRESENTATION DEFENSE

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CONTENTS

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Revison

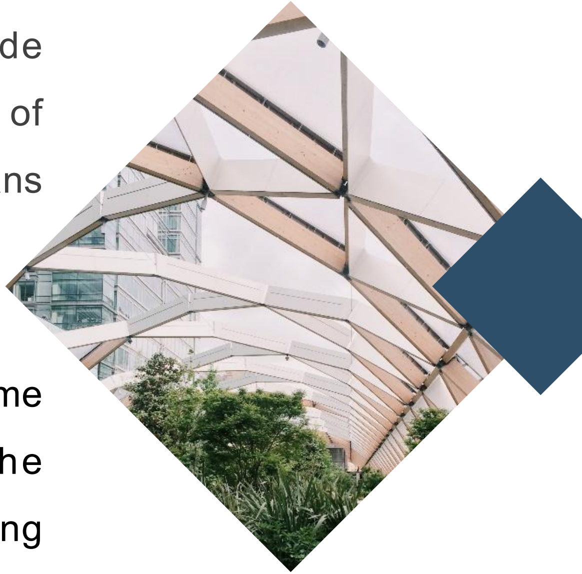
Introduction

Problem

- GAN has achieved great success in image generation today, but there are still some challenges. These include mode collapse, training instability, and evaluation of the quality of generated images. These problems limit the wide use of Gans in practical applications.

Solution

- In order to solve these problems, this project proposes some constructive methods. For example, by improving the architecture of the generator and discriminator, introducing regularization techniques and residual networks, and using adversarial training strategies (e.g. Wasserstein GAN).



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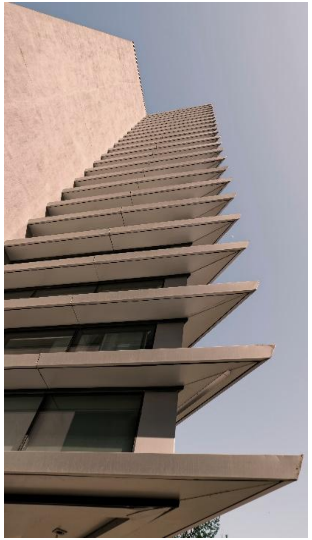
Background

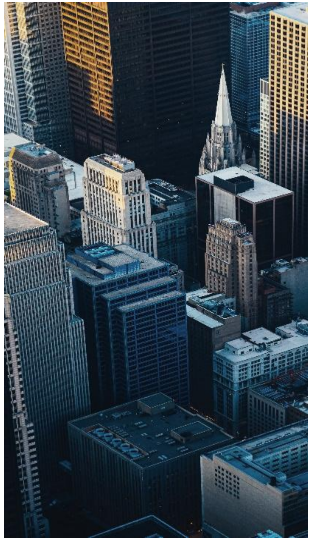
Background

Research Work



- Many works in GAN research focus on improving training stability and generated image quality.
- New loss function by Wasserstein GAN for better training stability and image quality.
- Self-attention mechanism by Self-Attention GAN for improved detail and global consistency.
- Residual networks in GAN structure for enhanced image quality.

Project Contribution



- Introducing residual networks into GAN structure to enhance the quality of generated images.
- Addressing challenges of training stability and generated image quality in GANs.
- Contributing to progress in the field of image generation through these improvements.
- Providing new ideas and methodologies for future GAN development.

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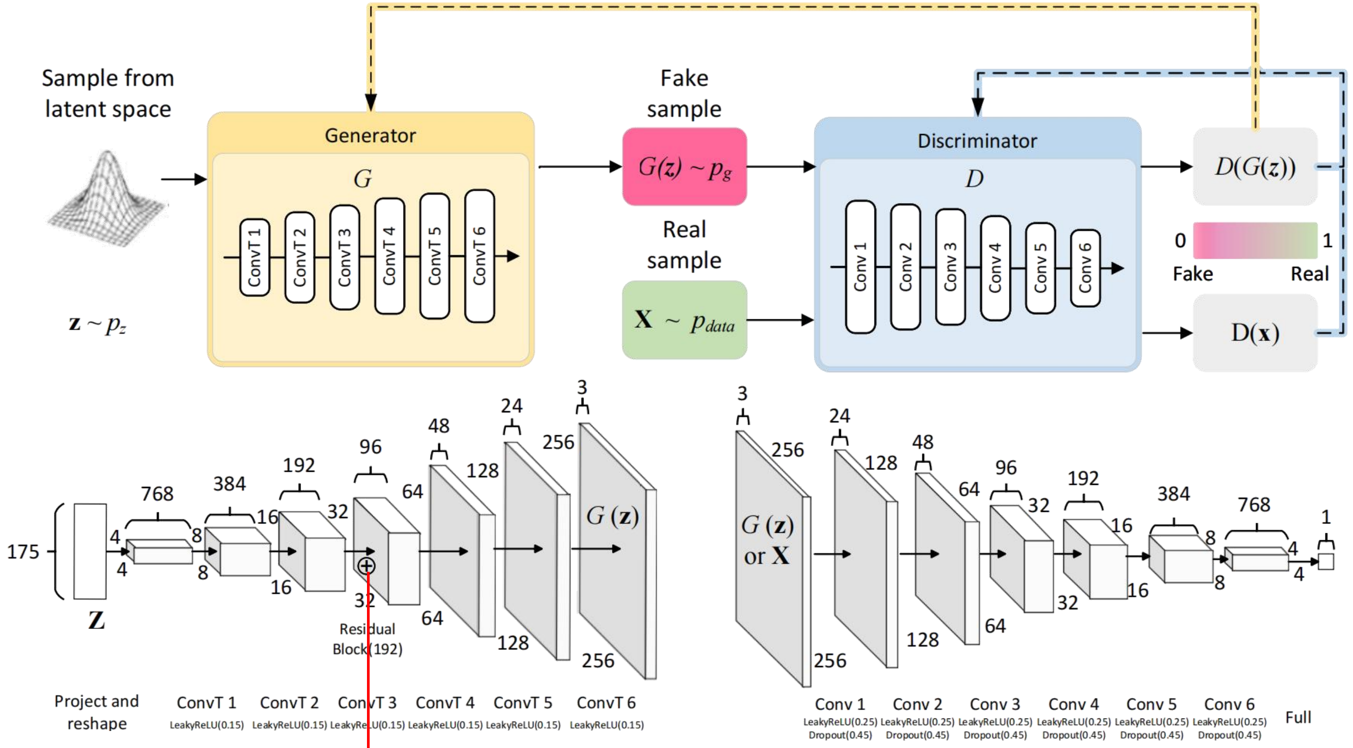
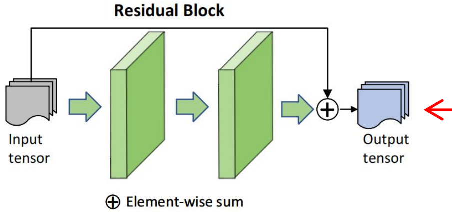
Architecture

Proposed Model



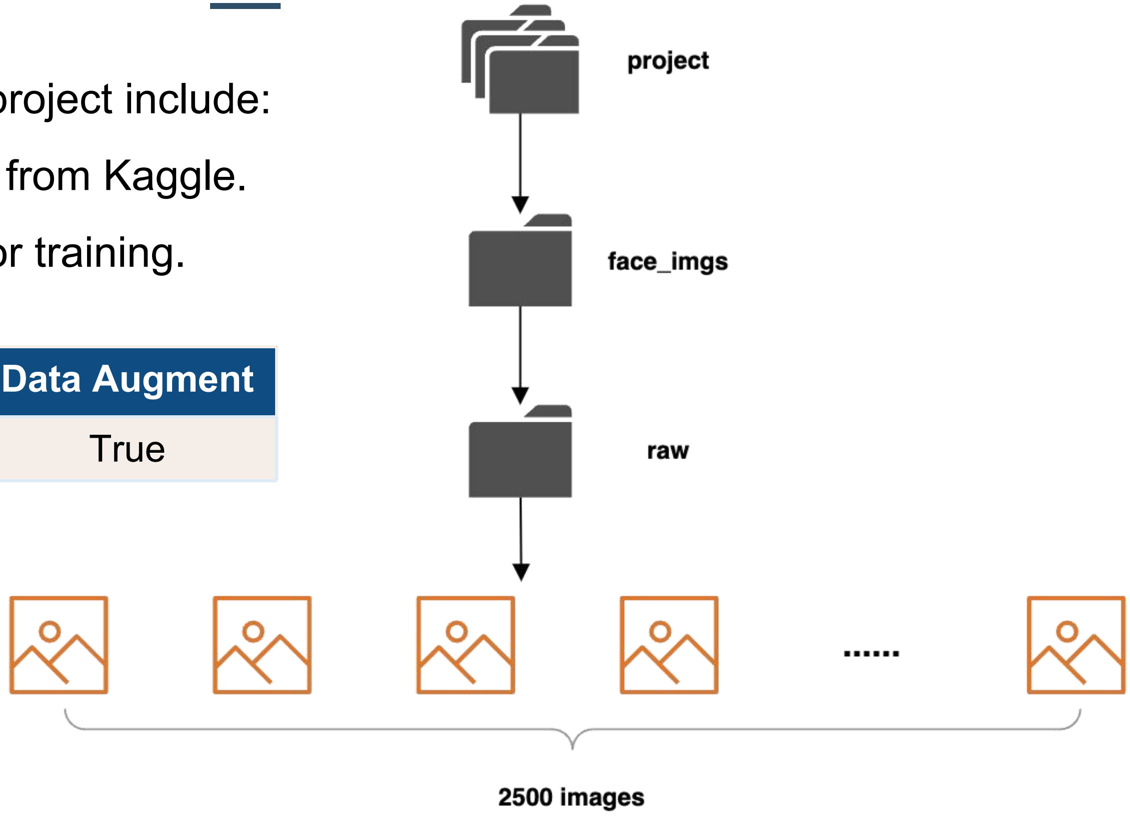


This model is based on DCGAN to improve. The model increases the depth of the network, introduces the residual network, and makes targeted adjustments to the hyperparameters.

Dataset

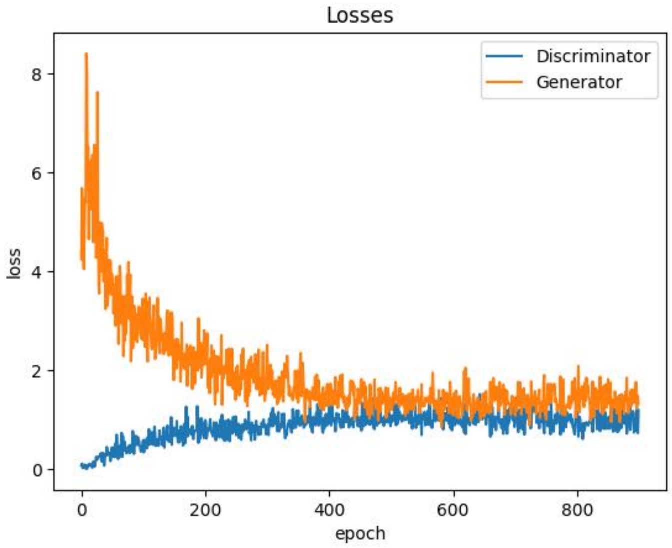
- The dataset structure of the project include:
- 2500 high quality face image from Kaggle.
- processed before it is used for training.

Batch Size	Resize	Data Augment
4	256 ✖ 256 ✖ 3	True



Research results display for first phase

In this stage, the modified model is used for pre-training, and the basic dataset (MNIST) is used to train the model. Finally, compare the training results of my improved DCGAN model with the original DCGAN.

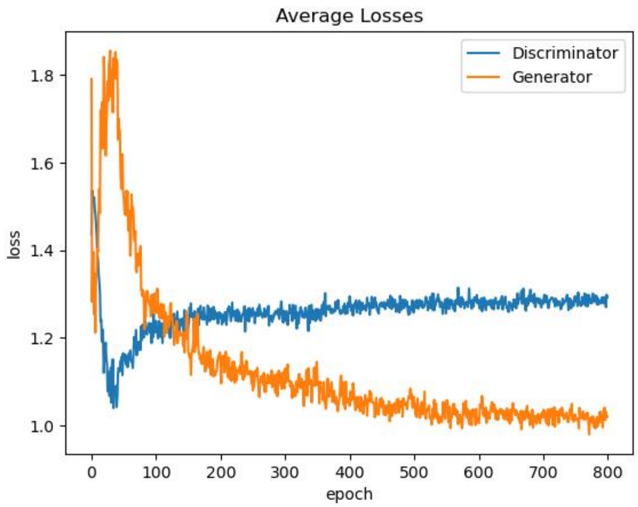


My DCGAN model

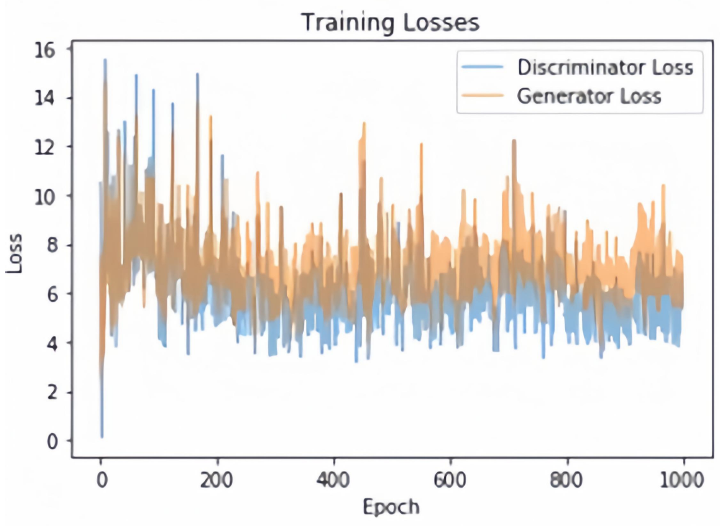
Oringinal DCGAN model

Research results display for second phase

At this stage, the high-definition face dataset mentioned above is used to continue training the model, and the DCGAN model improved by me is compared with the original DCGAN model.



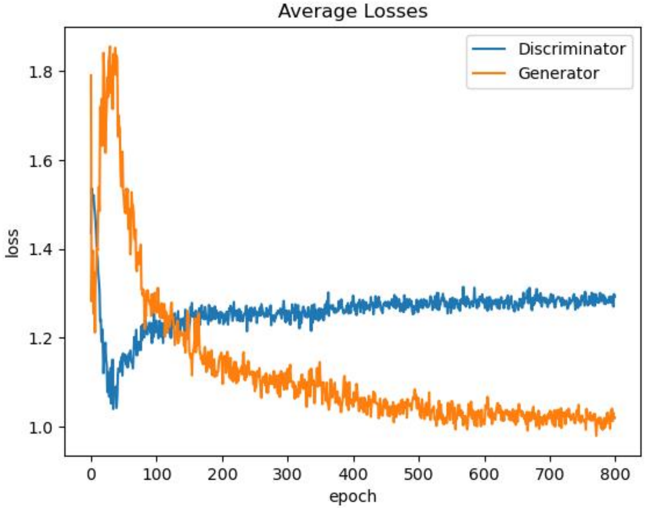
My DCGAN model



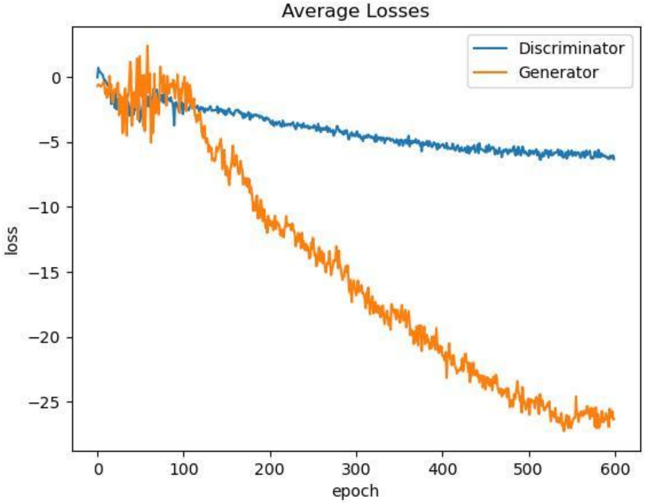
Oringinal DCGAN model

Research results display for third phase

In this stage, further exploration is carried out based on the improved model. The gradient penalty mechanism and a new loss function-Wasserstein loss are introduced. The new model is compared with the improved DCGAN model.

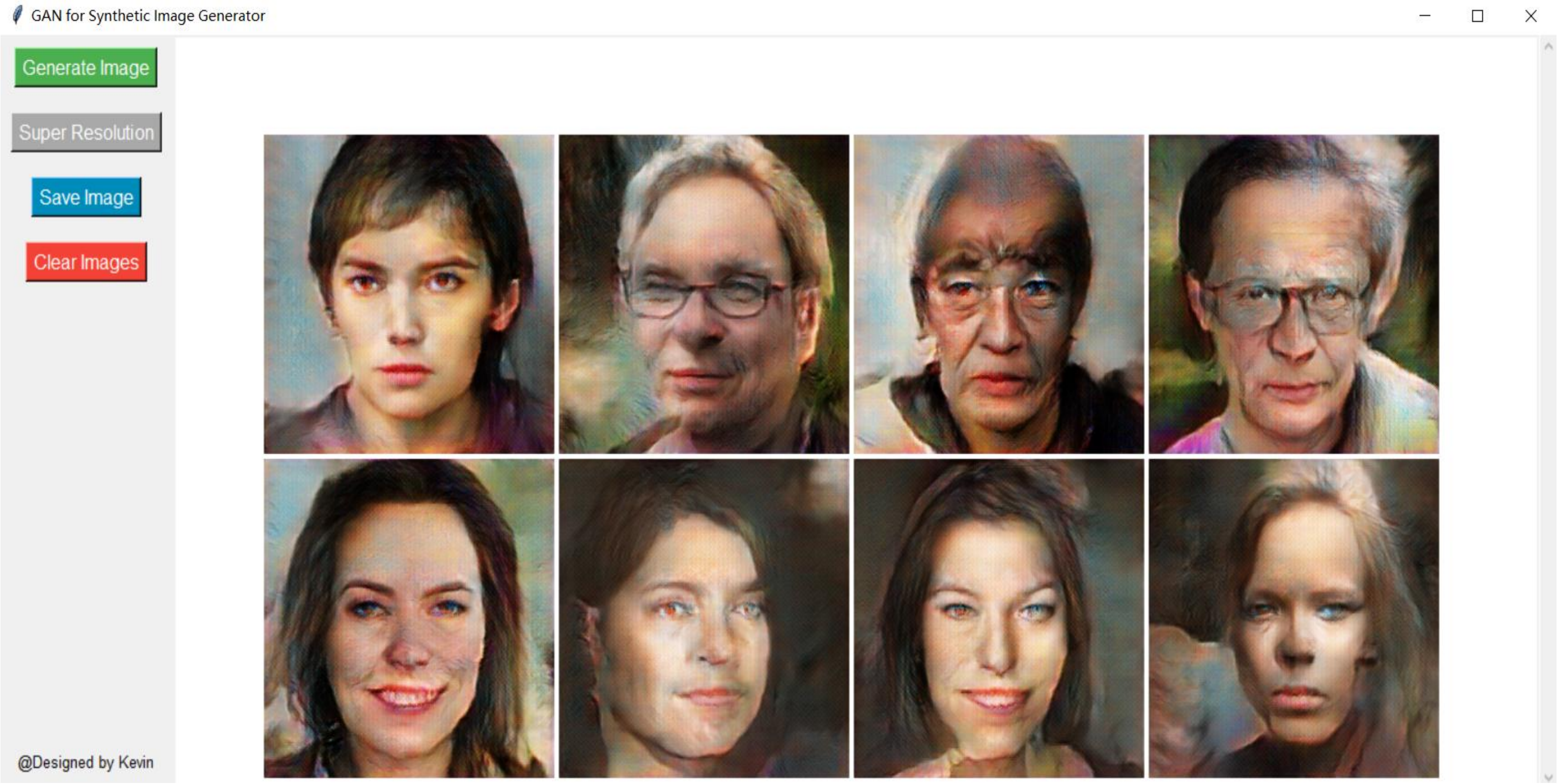


My DCGAN model



WGAN model

GUI Display



GAN for Synthetic Image Generator
Generate Image
Super Resolution
Save Image
Clear Images
@Designed by Kevin

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Limitation

Data Limitation

- The dataset is not large enough and the diversity is not rich. Currently only the face dataset is available.
- The quality of the dataset needs to be improved, and there is some slight noise in the dataset.
- The samples in the dataset have some deviations and are not uniform enough. For example, there are far fewer photos of faces with glasses in the dataset than without glasses.

Model Limitation

- Although the improved model has better performance than the original model, the improved model is not expressive enough, which makes the generated images still have obvious noise.
- The resolution of the synthetic images is relatively low, so it is not possible to generate HD images.
- There is a certain gap between the details of the synthetic image and the real image, which is easy to be distinguished.

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Future Work

Future Directions for improvement

- Optimize the model, try to improve the architecture of GAN model, use more advanced GAN model, such as StyleGAN model.
- Train models on better quality datasets and pay for professionally processed datasets.
- Introduce image super-resolution function. The images synthesized by the model are super-resolved, which helps to improve the details and quality of the synthesized images.

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Conclusion

- GANs have great potential for synthetic image generation.
- Several limitations need to be addressed to realize their full capabilities.
- Limitations include data-related challenges and inherent GAN model limitations.
- Addressing these limitations can improve robustness, adaptability, and quality of synthetic images.
- Future improvements can open up new possibilities for GAN applications in various domains.

Thank you

T H A N K S

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