Restoration of Historical Illustrations using Generative Adversarial Networks

Vincent Chin Wen Shen
B.Sc (Hons) in Computer Science
Asia Pacific University of Technology and Innovation
Kuala Lumpur, Malaysia
TP061209@mail.apu.edu.my

Murugananthan Velayutham
School of Computing
Asia Pacific Univeristy of Technology and Innovation
Kuala Lumpur, Malaysia
murugananthan@apu.edu.my

Abstract— Generative Adversarial Network (GANs) is widely implemented not just for image generation but also text, audio, video processing and more. To add on, methods of image restoration and enhancement such as semantic inpainting, out painting, filtering, denoising are achievable by GANs. This paper reviews theoretical basis of GANs in image generation, also known as image synthesis and possibilities of successful restoration of historical illustrations such as buildings, landmarks, cultural heritage that have been lost or demolished. By training GANs on relevant dataset of images, it can learn characteristics & features of dataset to generate desired results based on raw image as input. Theoretical knowledge about GANs and relevancy of study is elaborated. For methodology, random sampling and stratified sampling are applied for data collection with justifications together with limitations. The proposed system, HistoGAN restores damaged or incomplete images through image synthesis after being trained with large datasets. Performance of implementation is analyzed and evaluated to identify space of improvement to uplift performance. HistoGAN has the potential to be applicable in other fields such as historical research, architecture discovery, and education.

Keywords - Generative Adversarial Network, Image Synthesis, Image Restoration, Historical Illustrations, Cultural Heritage.

I. Introduction

Generative Adversarial Network (GANs) is one type of machine learning system that implements the contest of two main neural networks – a generator and a discriminator. These implementations allow GANs to imitate data distributions in different forms such as text, audio, images to videos. One of the neural networks, generator attempts to trick the discriminator network by creating realistic images from random noises. Random noises ensures that no identical images produced in generator. Simultaneously, discriminator tries to differentiate whether images are fake or real (Fig 1).

This makes up the term of 'adversarial' of GANs (Combettes, 2021). Every machine learning system requires training, same goes to GANs. In every training, generator gradually improves in creating real-like images and discriminator gets better in differentiating between training datasets and generator datasets. The training reaches equilibrium when discriminator fails to differentiate whether images are real or fake. Therefore, generative model that is capable of generating realistic images is achieved and discriminator is no longer required. Other than image synthesis mentioned above, other trained generative models can perform enhancement of images such as colorization, super- resolution, and style transfer.

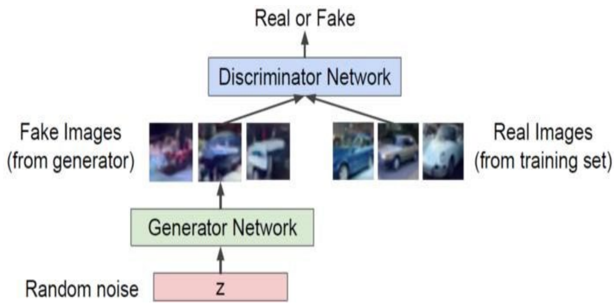

Fig 1. How generator and discriminator networks work.

Several procedures and processes are required to implement a working generative model that performs images synthesis focuses on historical illustrations. Firstly, architectureof generator and discriminator networks (Figure 1) is defined and sample dataset of 4000-5000 images of historic buildings is collected and pre-processed as input of generator. Secondly, loss functions for both networks are also defined. Loss function of generator uses binary cross-entropy loss between predicted labels and true labels toproduce as realistic images as sample dataset given. Loss function of discriminator also usessame loss between predicted labels by generator and true labels from dataset (Cheng,2022). Figure 2 shows the simplified process in building a basic GAN.

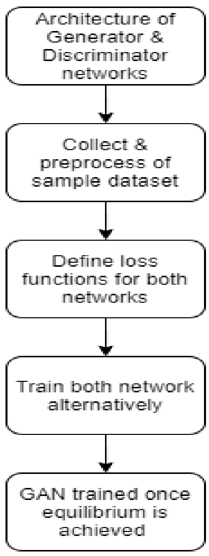

Fig 2. Process of building a basic GAN.

Output of labels by discriminator are 1(or close to 1) for real and 0 (or close to 0) forfake. Thirdly, both networks are trainedalternately where generator produces more realistic images while discriminator gets betterat differentiating them. Lastly, once equilibrium is achieved where output of discriminator is 0.5 which is undistinguishablebetween real of fake, this means that generatorhas learnt pattern and style relevant to dataset.When a damaged or incomplete raw image is inputted, generator can recover elements of raw image to look visually better and complete.

II. Literature Review

A. Research Domain

Machine Learning : GANs are part of the machine learning field that uses unsupervised learning to generate new data similar to a given dataset without any labeled output data, with the main objective of finding data patterns or structures (GeeksforGeeks, 2022a).

Image Synthesis : The main application of GANs is image synthesis where many types of GANs such as DCGANs, StyleGANs, BigGANs and more are different from each other in generation of images with different types and contexts (Jin et al, 2020c). Trained model can also be useful in other domains such as artifacts, artwork, and cultural studies.

Image Enhancement and Restora- tion : Next, image enhancement and restoration involve rebuilding low-quality, degraded, and damaged images. GANs is capable of generating new pixels that matches styles and context of original image with evaluation of discriminator network for restoration. In addition to image restoration, GANs can also be used for image enhancement such as increasing image resolution, colorization, colour correction and noise reduction (Yeh et al, 2018b). Quality of images can be improved without having to risk the modification of raw image.

Historical Research : Output of generative model aids historical research for archaeologists, historians in visualizing missing or damaged artifacts of buildings that were not fully documented. For example, visual representation of building artifacts based on historical context and existing knowledge allows historical events, cultures that have been lost in time to be preserved.

Architecture Engineering :Output of generative models can be used to visualize lost or damaged parts of historic buildings, allowing modern architects to understand and investigate initial appearance and structure of buildings (Fratini et al., 2011b). This evokes spaces of imagination in creating new designs and even reconstructing historic building that were lost or incomplete in the past. Different design possibilities can be achieved as a valuable tool to help us acknowledge better and appreciate architectural heritage of human civilization.

Education : Output of generative model which are restored images of historic buildings or landmarks that were lost can be included into educational materials, making learning process more engaging, interactive, and accessible for students. GANs is also capable of creating simulations for students to apply their imagination in a virtual environment that mirrors the real world.

B. Similar System

There are other researchers that implemented image synthesis using GANs.The first article with the title of Image Restoration with deep generative modelsmentions that most existing restoration methods depends on image prior that enforceslocal image consistency- in recovered image (Yeh et al, 2018b). Therefore, Raymond and the research team proposed to produce image prior in data-driven manner. Similar to proposed system, Raymond and his team implements unified framework based on MAPand generative adversarial nets.

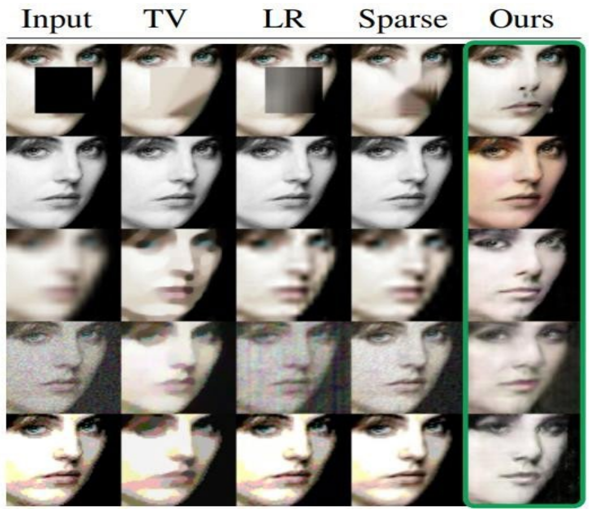

Fig 3. Image Restoration results of implementation by Raymond and his team.

Figure 3 shows results where each row represents semantic in painting, colorization, super-resolution, denoising and intensity quantization from top to bottom. Comparison of results to baseline approaches shows proposed method performs poorly but realisticfrom visual inspection when compared to other approaches.

Next, the second article, Physics-Based Generative Adversarial Models for Image Restoration and Beyond. In this article, Hishanand his team presented an algorithm directly fix numerous restoration type such as deblurring, dehazing and deraining of images (Pan et al, 2021b). As standard GAN is not performed well for this specific task, an algorithm that guides estimation of specific task within GAN framework under physics models is proposed and trained variety of restoration and low-level vision issues.

Fig 4. Comparison results among algorithms existed against proposed algorithms for deraining.

Figure 4 shows that proposed method outperforms state-of-art algorithms.Therefore, Hishan and his team suggested to include physics model in GAN that is beneficial for image restoration.

III. Problem Statement

Based on existing literature review, study shows that several problems have not been addressed and this research can help clarify them. According to both articles mentioned above, GANs that are trained on specific set ofsample data may not be able to generalize to other buildings or styles. This may affect the accuracy of outputs. For example, model is only capable of restoring of images during period of renaissance but not the stone age. Hence, proposed generative modelemphasizes on large data set for training to generalize results. General scope of evaluationplays an imperative role in building a good performing generative model that is versatile for variety of needs.

Secondly, sample data of generator is also crucial to provide high quality training of GANs. Generating high-quality images thatare visually realistic and detailed is a challenge for the model to generate images with realistic textures, lightning and other details that represents the historic building accurately. Fortunately, there many images of historicbuilding preserved until today in various formats. Online sources like The Internet Archive and Flickr have more than 12 million historical copyright-free images (Kelion, 2014). With current technologies, digitalimages can be collected from different forms as sample data. Therefore, quality of sample data for GANs should be emphasized throughout the construction process ofgenerative model.

Thirdly, GANs are computationally complex models that requires significant computing resources to train and generate images. GAN from both articles mentioned before were built completely from scratch with many team members working together. Therefore, implementation of proposed system from scratch could be time-consumingand overwhelming for a small team. Result ofimplementation might be inaccurate without cross-validation between programmers. This could also limit the scalability of built model especially when synthesizing images in large quantities. To overcome this, there are many open-source libraries that make building generative model easier such as CycleGAN, PyTorch-based library for image translation tasks (GeeksforGeeks, 2022a) and GANomalydesigned for anomaly detection in images (Akcay, 2018). Both of these libraries have large communities of users and developersthat could support implementation of proposed system.

IV. Research Aim, Objectives, Questions and Significance

Research Aim

The main aim of this research is to restoreimages by producing high-quality, realistic images of historic buildings, landmarks through implementation of GenerativeAdversarial Network (GANs) to be used for wide rage of purposes such as preservation, research purpose, cultural heritage, and education.

Research Objectives

In order to achieve research aim, a numberof objectives are formulated. Firstly, to completely acknowledge theoretical basis of GANs from top to bottom. Planning of systemsuch as architecture of neural networks in mustbe done well terms of computability and efficiency. This can be done by studying codefrom open-source libraries and referring to examples of other relevant research papers. Secondly, to accurately generate high- quality images of relevant images. Scope of model is generalized to cover all period of historical chronology. Large amount of data vary from different timeline plays an important role during implementation. Collected sample data must undergo pre- processing such as data cleaning.

Thirdly, to provide comprehensive understanding of historic buildings and architecture. Heritage buildings are crucial to human perception of culture and identity through time. For example, renaissance period of European civilization during the 14th century. History and relevant knowledge are studied and analysed as well. Next, to evaluate performance of GAN models by comparing between different models with their effectiveness. During the process of implementation, outcome of prototype is constantly recorded and reviewedbased on statistics of other articles that uses similar concept.

Nevertheless, to provide interactive platform for visualization of model outputs. Completed generative model can be integratedinto web compatible formats such as web APIto make API calls based on user inputs (GeeksforGeeks, 2020). Integrated website can be deployed to web server or hosting platform for people to access and interact with system.

Research Questions

There are few questions that arises in the context of proposed system.

1. How can GANs be trained to generate images of historic buildings and architecture with high accuracy and distinct styles or eras such as visual of building that may have looked in the past or in the future?

2. What factors influence the quality of the generated images, such as the size and type of the training dataset, the architecture of the GAN?

3. How well can GANs be used to fill in missing or incomplete information in images of historic buildings/architecture, such as missing components or interiors?

4. What are the possibilities GANs be used to augment or enhance existing images of historic buildings/architecture, such as by increasing their resolution or sharpness?

5. Can GANs be used to detect and correct errors or inconsistencies in images of historic buildings/architecture, such as incorrect coloration or misorientation of elements?

6. What ethical considerations involved in using GANs for image synthesis of historic buildings/architecture, such as the validity of the

generated images or the potential for misuse like falsification and deep fakes?

Research Significance

Research of proposed system explores thepossibility of visualization that refurbishes important information not just culturalheritage but also knowledge from images thatwere lost or incomplete in the past. Restored images that are accurate can be fully documented to be kept for upcoming generations. Well-trained generative model can make educational materials more interactive and interesting. For example, historical images created can be used in teaching architectural history through visuals that was previously inaccessible without GANs.

GANs makes image synthesis cost and time saving in the long term compared to physical illustration that is more overwhelming. GANs also provides easy access for public to access system virtually through websites. Reverse engineering can be performed through restored images that consist of undiscovered elements that could be useful for potential scientific research. This acts as a toolfor relevant researchers in exploring and analyzing valuable information for insights. For instance, restored image that consist of interior structure of buildings at the period of renaissance can inspire architectural concepts and uncover valuable data.

The existence of GANs unleashes limitless possibilities that can also be beneficial in wide range of fields such as medical, engineering and even literature.

V. Methodology

Overall methodology approach requires special approach that includes in-depth research, use case studies and similar systemsfrom domains implemented by other researchers. As most up-to-date information that is relevant to the proposed system are available online, many journal articles thatcovers field of study such as historical chronology, architecture design, deep learningwas reviewed. Other than that, method of datacollection is also essential.

The combination of random sampling and stratified sampling methods is suitable for data collection of this study. In random sampling, data is selected randomly from entire population to ensure diversity in sample. This helps the model to learn variety of features from different various of samples that diversifies training of dataset. Stratified sampling is also used that involves partitioning of population into smaller, homogeneous subgroups, each as a sample. This method ensures samples includes representative examples from distinct architectural styles from all range periods of history timeline.

Combination of both sampling methods facilitate more comprehensive and diverse sample to be used as dataset for GAN training. Moving on, core of proposed system which is the model of GAN is studied to choose suitable GAN architecture such as ProgressiveGAN, StyelGAN, BigGAN (Ddlee, 2019). Size and quality of dataset, capability of computation and desired outcomes are also considered before selection.

Next, results of proposed system will be evaluated based on the quality and reliability of generated images. Method of analysis such as structural similarity index (SSIM), Frechet Inception Distance (FID) and user investigation will be used (SSIM: Structural Similarity Index | Imatest, n.d.). Results of analysis and interpretation would help in improving training process, tweaking parameters to enhance quality of results.

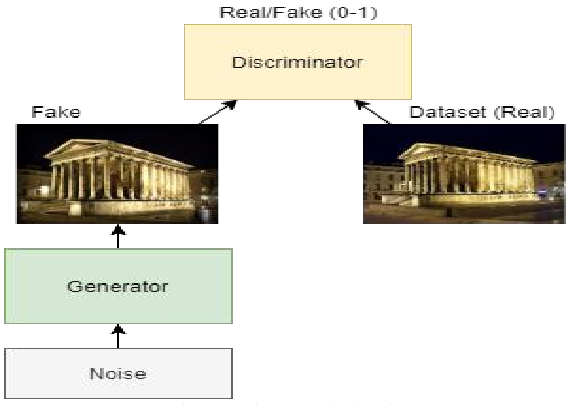

Fig 5. Both networks in HistoGAN.

This approach is chosen to clarify the specifications and requirements from theoretical to technical basis for acknowledgement of study. It also ensures proper implementation of system through in- depth research with the goal of archiving desired results. However, few potential limitations might arise from this methodology. Firstly, quality of dataset could be limited. This impacts the outcome of proposed system to generate blurry, unrealistic, disorganized, and consistent images. In certain scenarios, images for training might be unobtainable due to confidentiality of preservation from relevant authorities.

The second limitation goes to model selection as all models has respective advantages and disadvantages over one another. Trade-off between computation capability, model complexity and architecture effectiveness could occur. Thirdly, bias and fairness from training data and architecture of system might reflect generated images to produce inconsistent, unwanted results.

In additional, the availability of computational resources in building the proposed system. GAN training can be computationally intensive that demands high- end graphic processing unit (GPU) with adequate memory and processing power. Accessibility of high-end GPUs could be limited as they are costly and hard to obtain.

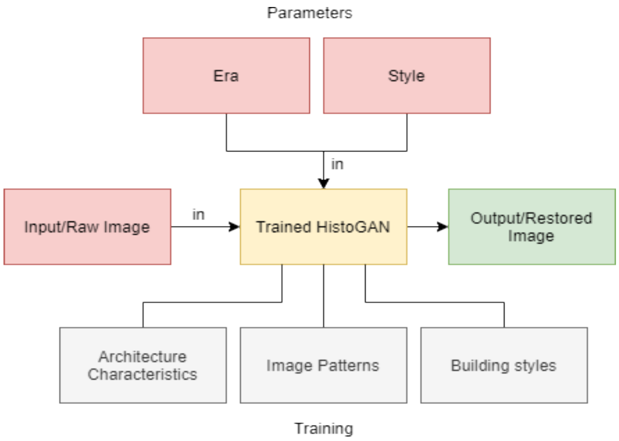

Fig 6. System design of HistoGAN.

Lastly, ethical, and legal issues where output of proposed system could lead to copyright infringement, intellectual property rights, and violate cultural heritage protection.There are possibilities that generated images might be controversial or offensive to relevantentities that oppose terminology of proposed system.

VI. Overview of the Proposed System

Proposed system, HistoGAN that is built on top of GANs can restore images of historicbuilding of any period from history based on image and text as input parameters. Similar tomost existing GANs, HistoGAN consist oftwo main neural networks which are generatorand discriminator (Figure 5). Generator generates new images and discriminator attempts to correctly identify whether image is real or fake. Architecture of HistoGAN is defined based on preference of task to be performed. Existing architectures like ProgressiveGAN, StyelGAN, BigGAN are referred during implementation. Total of 4000-5000 images of historic buildings from different era of civilization is collected through online sources as training data of model. Obtained dataset undergoes necessary cleaning and pre- processing before inputting into generator network.

To generate images of historic buildings and architectures, HistoGAN is trained on large dataset of relevant images to learn the patterns and styles of dataset so that the systemhas the skillset to synthesis new image that restore or enhance the original image. With bigger and diverse training dataset and more complex architecture of model, quality of images restored can be improved.

As shown in figure 6, trained model that learnt architecture characteristics, patterns and styles of historic buildings is ready to be fed images that are damaged for restoration. At thesame time, parameters such as period of generation and style of restoration is also prompted to user. For instance, user can choose to restore image based on generation of civilization from Mesopotamia to Ancient Greek. User can also change the restoration style such as default, smoothing, denoise, high-resolution and so on.

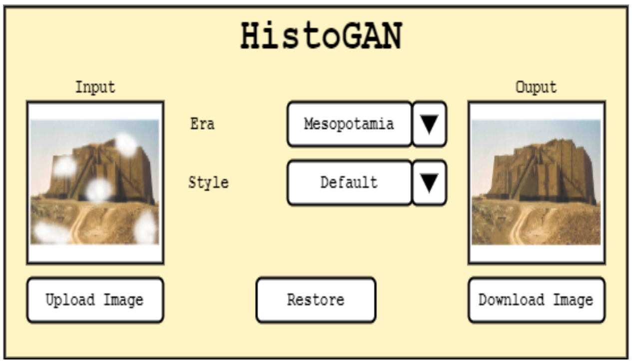

Fig 7. User interface of HistoGAN (Prototype).

When parameters are adjusted accordingly, user can start restoring image byclicking restore button. After restoration process completes, restored image based on selected era and style is outputted from the model (Figure 7). Every Results of output is collected for evaluation purposes.

VII. Conclusion

Theoretical and technical knowledge of GANS has been explored and studied by various approaches. There are almost countless ways to implement and train GANs and the use of GANs with the objective of restoring historical illustrations accurately by virtual reconstructions of building is very impactful for preservation as historical artifacts, scientific discovery, educational purposes and even tourism. Idea of proposed system provides a promising and innovative approach in preserving architectural heritage of the world.

References

Akcay, S. (2018, May 17). GANomaly: Semi-Supervised Anomaly Detection via Adversarial Training. *arXiv.org*. https://arxiv.org/abs/1805.06725

Cheng, T. (2022, January 6). Building a GAN with PyTorch - Towards Data Science. *Medium*. Retrieved February 2, 2023, from https://towardsdatascience.com/building-a-gan-with-pytorch-237b4b07ca9a

Combettes, S. (2021, December 16). A basic intro to GANs (Generative Adversarial Networks). *Medium*. Retrieved February 2, 2023, from https://towardsdatascience.com/a-basic-intro-to-gans-generative-adversarial-networks-c62acbcefff3

Ddlee, D. (2019, September). GANs for Image Generation: ProGAN, SAGAN, BigGAN, StyleGAN. *CV Notes*. Retrieved February 2, 2023, from https://cvnote.ddlee.cc/2019/09/15/progan-sagan-biggan-stylegan

Fratini, F., Pecchioni, E., Rovero, L., & Tonietti, U. (2011). The earth in the architecture of the historical centre of Lamezia Terme (Italy): Characterization for restoration. *Applied Clay Science, 53*(3), 509–516. https://doi.org/10.1016/j.clay.2010.11.007

GeeksforGeeks. (2020, May 31). What is Web API and why we use it. *GeeksforGeeks*. https://www.geeksforgeeks.org/what-is-web-api-and-why-we-use-it/

GeeksforGeeks. (2022, July 4). Generative Adversarial Networks GANs An Introduction. *GeeksforGeeks*. Retrieved February 2, 2023, from https://www.geeksforgeeks.org/generative-adversarial-networks-gans-an-introduction/

GeeksforGeeks. (2022, June 23). Cycle Generative Adversarial Network CycleGAN. *GeeksforGeeks*. https://www.geeksforgeeks.org/cycle-generative-adversarial-network-cyclegan-2/

Jin, L., Tan, F., & Jiang, S. (2020). Generative Adversarial Network Technologies and Applications in Computer Vision. *Computational Intelligence and Neuroscience, 2020*, 1–17. https://doi.org/10.1155/2020/1459107

Kelion, B. L. (2014, August 29). Millions of historical images posted to Flickr. *BBC News*. https://www.bbc.com/news/technology-28976849

Khodeir, L. M., Aly, D., & Tarek, S. (2016). Integrating HBIM (Heritage Building Information Modeling) Tools in the Application of Sustainable Retrofitting of Heritage Buildings in Egypt. *Procedia Environmental Sciences, 34*, 258–270. https://doi.org/10.1016/j.proenv.2016.04.024

Pan, J., Dong, J., Liu, Y., Zhang, J., Ren, J., Tang, J., Tai, Y. W., & Yang, M. H. (2021). Physics-Based Generative Adversarial Models for Image Restoration and Beyond. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 43*(7), 2449–2462. https://doi.org/10.1109/tpami.2020.2969348

SSIM: Structural Similarity Index | Imatest. (n.d.). Imatest. https://www.imatest.com/docs/ssim/

Van Hoorick, B. (2019). Image Outpainting and Harmonization using Generative Adversarial Networks. *ArXiv: Computer Vision and Pattern Recognition*. https://arxiv.org/pdf/1912.10960.pdf

Yeh, R. A., Lim, T. Y., Chen, C., Schwing, A. G., Hasegawa-Johnson, M., & Do, M. (2018). Image Restoration with Deep Generative Models. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. https://doi.org/10.1109/icassp.2018.8462317