

Methods for applying 2D Architectural Styles to
3D Architectural Models through Machine
Learning

Applying historical architectural features to modern buildings with
Neural Style Transfer

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Abstract

This dissertation explores the potential of applying 2D architectural styles to 3D architectural models via machine learning techniques, with an impact that could potentially contribute to heritage conservation and the video game industry. Through a systematic approach, the research goes through a variety of machine learning models, including Generative Adversarial Networks (GANs) and style transfer methodologies, alongside 3D scanning tools such as Agisoft Metashape and Adobe Substance 3D Stager. This study investigates the intricacies of style translation from two-dimensional facades to three-dimensional structures, assessing the viability and accuracy of these transformations.

The research question tests the feasibility of using existing machine learning packages and methods to apply 2D architectural styles to 3D models of buildings. This involves a methodological exploration of different scripts and approaches, leading to a refined process finishing with the application of styles to various architectural models. Tests include initial 2D-to-3D style applications, multi-view style transfers, and rendering enhancements to facilitate improved visual output.

Through the tested methods, there were significant insights into the inputs' effects on model training and the resulting impact on the built environment. The research starts from early experiments with 2D style applications, leading to the implementation of multi-view style transfer techniques. Limitations and gaps within the current studies are identified, offering an understanding of the challenges faced. The discussion also includes unsuccessful trials, such as the 3D reconstruction of the model in Agisoft Metashape, and the subsequent shift to alternative methods like Adobe Substance 3D Stager for textural enhancements.

This dissertation contributes to the field through a detailed explanation of the procedures and results obtained from the novel application of machine learning to architectural visualization. It shows the repetitive journey of experimentation, revealing both successes and unsuccessful trials. The study's outcomes have significant implications for the digitization of architectural heritage and the realistic rendering of historical structures within modern digital platforms.

Section 1

Introduction

In any domain possible, change can be challenging. It is hard to shift from known, used procedures and methods to new ones, no matter what they are. The convergence of technology and traditional practices resulted in transformative changes across various fields, and the field of the Built Environment is no exception. Historically, architecture has progressed through a series of evolutionary steps, depicted in Figure 1 by S. Chaillouⁱ. The timeline focuses on innovations, inventions, and theoretical advances in architecture. The introduction of Artificial Intelligence marks the advent this dissertation is focused on.

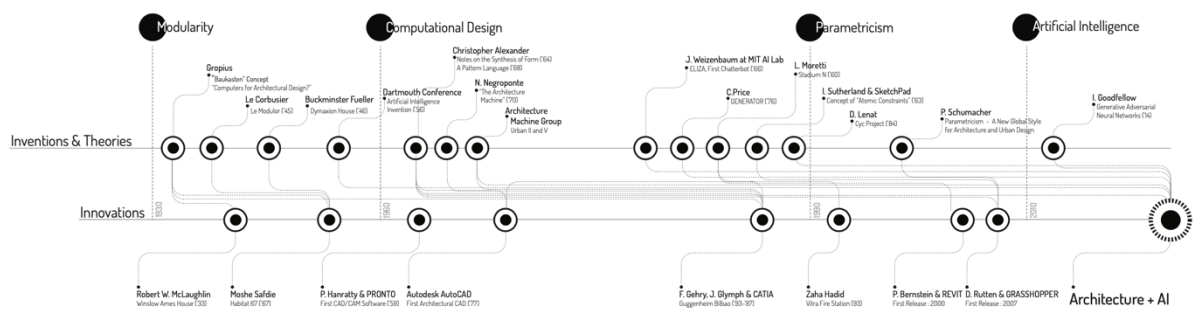


Figure 1. *Innovations and Inventions & Theories in Architecture*, developed by S. Chaillou, 2019ⁱⁱ.

Artificial Intelligence and Machine Learning were built on top of the introduction of CAAD (Computer-Aided Architectural Design), in the 1960s. During that time, there was a transition from manual drafting to computer-aided design with basic drawing and design functionalities. It has also laid the groundwork for the integration of Building Information Modelling (BIM), for advancements and progress in 3D modelling. From this point on, new parametric and generative design methodologies were introduced, as well as the incorporation of environmental, energy efficiency, and urban context data analysis and simulation into design processes.

Research Aims and Objectives

The recent discoveries and changes in this domain are exciting and pave the way to more challenges, when combining Computer Science with Architecture. As most research focuses on using different kinds of neural network models for style transferring, generating floor plans, and being applied to different scales, from entire cities to neighbourhoods and buildingsⁱⁱⁱ, a question that can come to mind is: How can 2D architectural styles be aptly applied to 3D models of structures using accessible technology and methodologies? This dissertation will focus on the details of this intricate process, aiming to enhance the application of machine learning models within the Built Environment as well as finding a method that would manage to transfer the features and characteristics of a historical building to a 3D model of a structure. A challenge that presented itself when carrying out this work was transferring the style from a 2D image to a 3D model, particularly a building.

Focused on this aim, the objectives are the following:

1. Utilising readily available sample datasets, e.g., 3D datasets of significant urban landscapes and architectural styles, focused on features and characteristics.
2. Engaging with advanced machine learning models, such as GANs and Neural Style Transfer, but also with 3D Scanning tools, such as Agisoft Metashape and Adobe Substance 3D Stager.
3. Identifying and critically analyzing the existing gaps and limitations in current research methodologies, as well as understanding the intricacies involved in training these models.
4. Generating substantive results and acknowledging the impact this research would have on the built environment.

By the end of this investigative process, the ambition is to distil a procedural methodology capable of applying historical architectural styles to new builds. Along with this experimental journey, some impacts could arise, such as redefining heritage preservation, contributing to the cultural resonance of urban environments, and the enhancement of a city's visual narrative.

Section 2

Generative Adversative Networks

The thought process for this dissertation started from the want to see any further connections between Neural Networks and the field of Architecture. The literature review starts from the earliest publication on GANs, developed by I. Goodfellow et al, 2014^{iv}, where generative models started to use an adversarial process, namely the Generator and Discriminator parts of the model, the process visible in Figure 2. According to the paper, this process assures that the performance of backpropagation is better, leading to more accurate results.

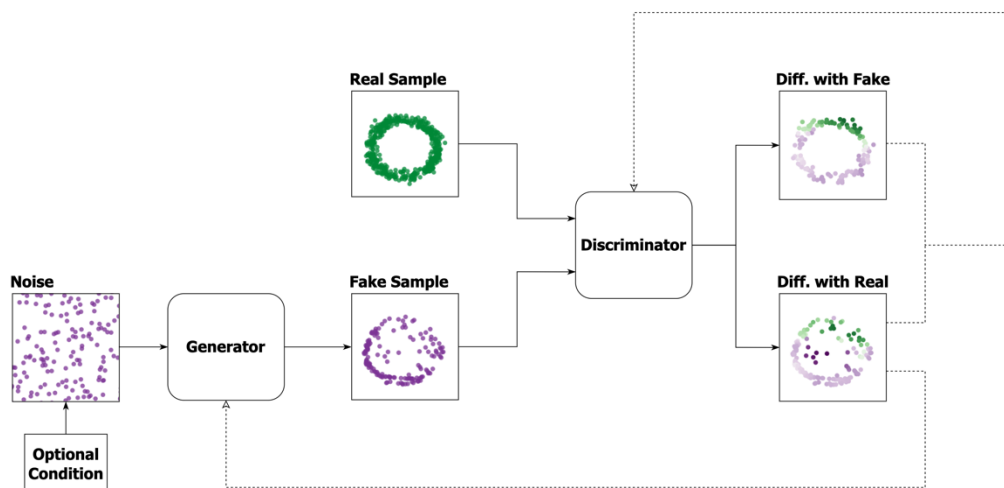


Figure 2. The architecture of GAN, figure developed by A. N. Wu et al, 2022^v.

Going further, Generative Adversarial Networks are being used continuously nowadays in Architecture, being the chosen model for complex studies, such as neural style transfer for 3D meshes. H. Kang et al, 2023^{vi}, have used a pre-trained MeshNet model to extract distinct content and style features from 3D models. This research also shows deep learning advancements in 3D modelling, where GANs are applied in urban design. This can further lead to revolutionising visualisations and decision-making in architectural design. Developments in this field were also made by H. Zhang, 2019^{vii}, using StyleGAN for generating architectural designs. The study demonstrated that there is potential in using GANs when generating 3D models from 2D data, paving the way for new possibilities for architectural planning and visualisation. Moreover, machine learning algorithms were also used for analysing and transferring style in architecture, according to H. Zhang, 2019^{viii}, the

study achieved style transfer at high resolutions, enhancing the quality and detail of the 3D models used in the project. Both studies have used StyleGANs as starting points, but other types of GANs such as CycleGAN proved extremely useful for this area of research.

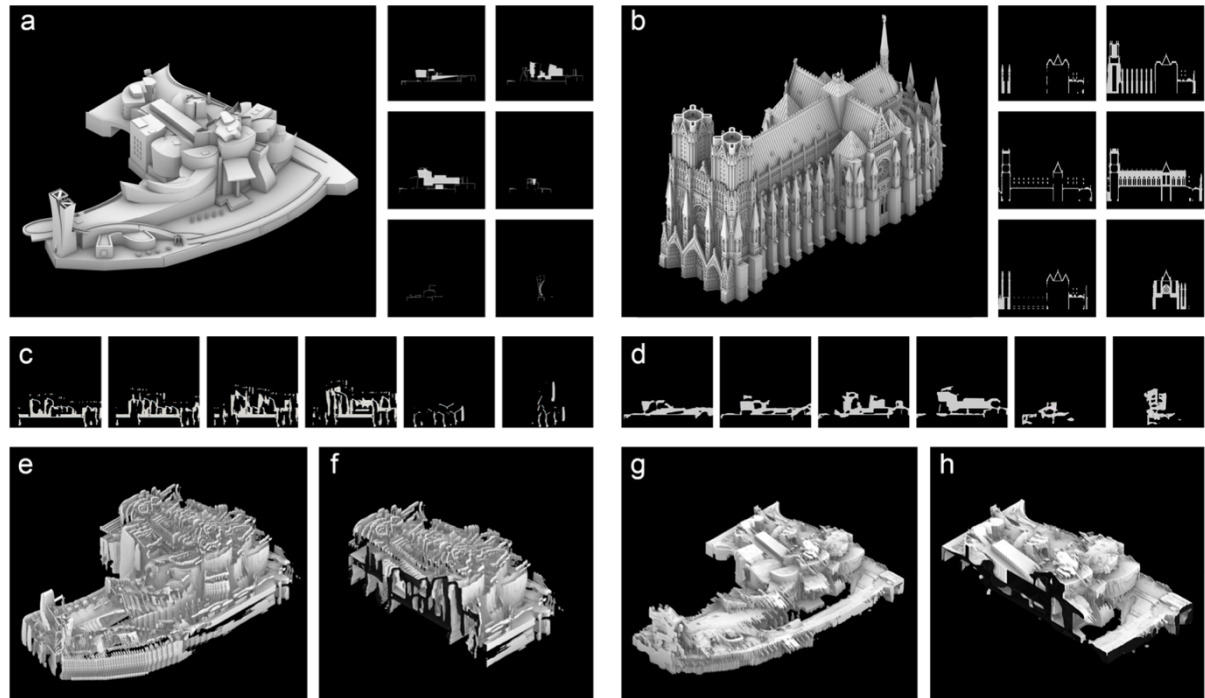


Figure 3. Style transfer results from the 3D-to-3D model, using CycleGAN and pix2pix. Developed by H. Zhang, 2019^{ix}.

Based on the chosen research question, there is scarce progress in matching a 2D image to a 3D model. However, F. Wang et al, 2015^x, managed to successfully match 2D sketches to 3D models using Siamese Convolutional Neural Networks by training two separate networks for sketches and 3D model views, allowing effective matching between these domains. Matching this with the Built Environment, this study proves relevant due to the need for rapid and accurate conversion of ideas into models.

Single-View Neural Style Transfer

Neural style transfer is a technique that can extract features from a content image and a style image, based on a pre-trained convolutional neural network. The algorithm focuses on reconstructions from the style features, which produce texturized versions of the input image that capture its general appearance in terms of colour and localised structures^{xi}. It was

introduced by L. Gatys et al, 2015, and its architecture can be seen in Figure 4. This technique is split into two types: optimization-based methods and feed-forward methods. Optimisation-based methods use an iterative process to minimise content and style discrepancies, usually using a Gram matrix to capture and recreate style features. While this method can be very precise, leans toward being computationally intensive. Feed-forward methods, on the other hand, have a quicker style application, using neural networks to transfer style in a single forward pass. The methods use Adaptive Instance Normalization (AdaIN) layers, which adjust the mean and variance of content features to match those of the style features dynamically. It is very flexible and quicker, but the level of accuracy can drop when compared to the optimisation-based methods.

Recent advancements have focused on refining these processes, such as Whitening and Colouring Transformations (WCT), enhancing the adaptability of style transfers by manipulating statistical layers to match feature distributions more closely, offering real-time capabilities, and integrating depth information for more nuanced transfers.

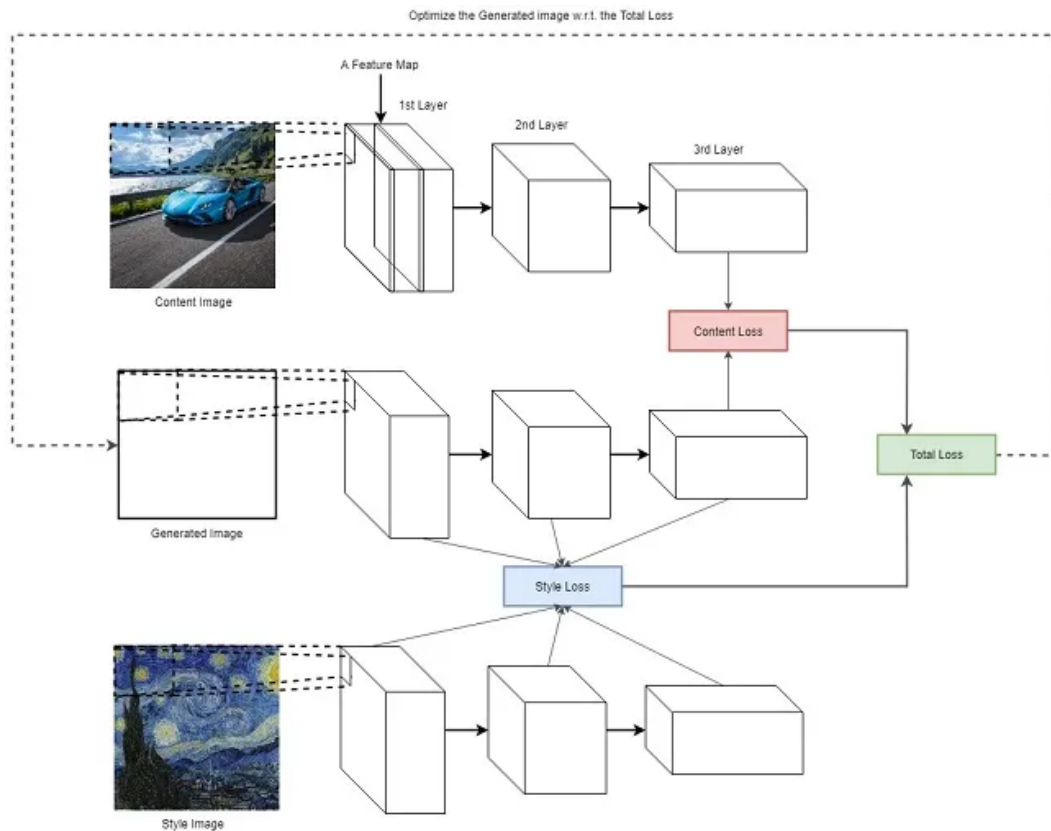


Figure 4. The architecture of the Neural Style Transfer model.^{xii}

3D Style Transfer

3D style transfer aims to apply artistic effects to 3D scenes from multiple viewpoints. Prior methods use different 3D scene representations like point clouds, triangle meshes, or radiance fields as neural network inputs for stylization. While some use stylized 3D point clouds processed through convolutional renderers, others apply style transfer to mesh reconstructions or utilize radiance fields for high-density, real-world scene view synthesis. Yet, these require dense coverage for accurate field reconstruction and struggle with baseline shifts in few-shot learning approaches.

Advancements focus on novel-view synthesis and mesh construction of various 3D models after performing the style transfer, using a flexible approach that does not rely on precomputed 3D data or dense view coverage. More research is focused on addressing the quality of stylised 3D renderings across different perspectives, to then be used in a style transfer algorithm.^{xiii} Other methods include reconstruction and photorealistic rendering from novel viewpoints, focusing on transferring styles specifically to textures, colours, and other elements within the 3D scenes, which is a significant improvement in controlling the aesthetic presentation of 3D environments.^{xiv}

Recent challenges include achieving consistency across multiple views, managing computational efficiency, and preserving the structural integrity of 3D models during the style transfer process. Based on the challenges of this field, the direction and methodology of this research project became clear. Ensuring style coherence across different renders of a 3D model with different lighting conditions can be complex, especially when thinking of not compromising the original 3D geometry. When thinking of this, incorporating advanced 3D modelling tools can significantly enhance the 3D style transfer process, which paved the way to working with multiple pieces of software, creating and refining 3D models through different approaches.

Section 3

Methodology

For this research, two ways were explored. The first one includes working with both 3D models and 2D images as inputs, to then model a Generative Adversarial Network for the blending process of the two. The second one will work with renders of the 3D model, namely Multi-view Style Transfer, and 2D images, and follow the same process as for the first test. The goal for both is to have an output that will essentially take the style of the 2D images and use it on a 3D model, which would essentially help with preserving a city's style by keeping the same historical architectural style for new builds as well.

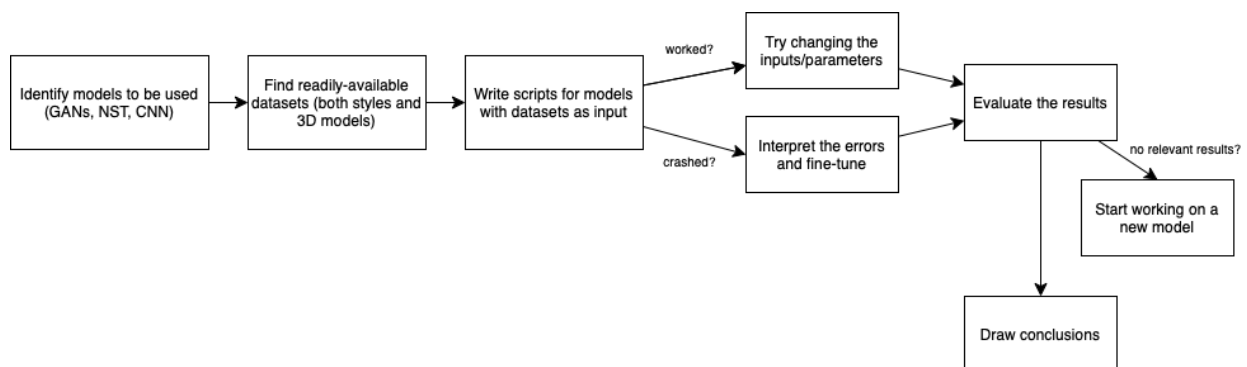


Figure 5. Study design of the project.

Starting from this point, a study design was generated in Figure 5. The models are first identified. Afterwards, datasets of architectural styles and 3D models were found, to be used as inputs for the models. Scripts were then generated for each model, using the datasets as inputs; if the code worked, the parameters could be slightly tweaked for better performance – if not, errors were interpreted and different neural networks could be used, to identify what would work best with this type of inputs.

When working with 3D models and using them as input, the study design can be seen in Figure 6. The model will be converted into an appropriate data structure that can be read by the model, normalised, and transformed into a chosen representation, e.g., mesh or point cloud. At the same time, the 2D images will also be used as input in the model and transformed into a chosen representation, working mostly with the sizing. Finally, the Generative Adversarial Network model is created, so the Generator and Discriminator parts

of the model, and loss functions are defined. All this data is then loaded into the algorithm, where it will be trained, fine-tuned and the results evaluated. The whole process can be lengthy, especially when working with high-performance models.

At the same time, for Multi-view Style Transfer, the study design can be seen in Figure 7. It follows a similar course as in Figure 6, but this time, the model is transformed into renders, and style transfer is then carried out for each of them. The results are then evaluated, and a dataset is generated out of the outputs to try to reconstruct the 3D model using 3D modelling software.

Generative Adversarial Networks Algorithm

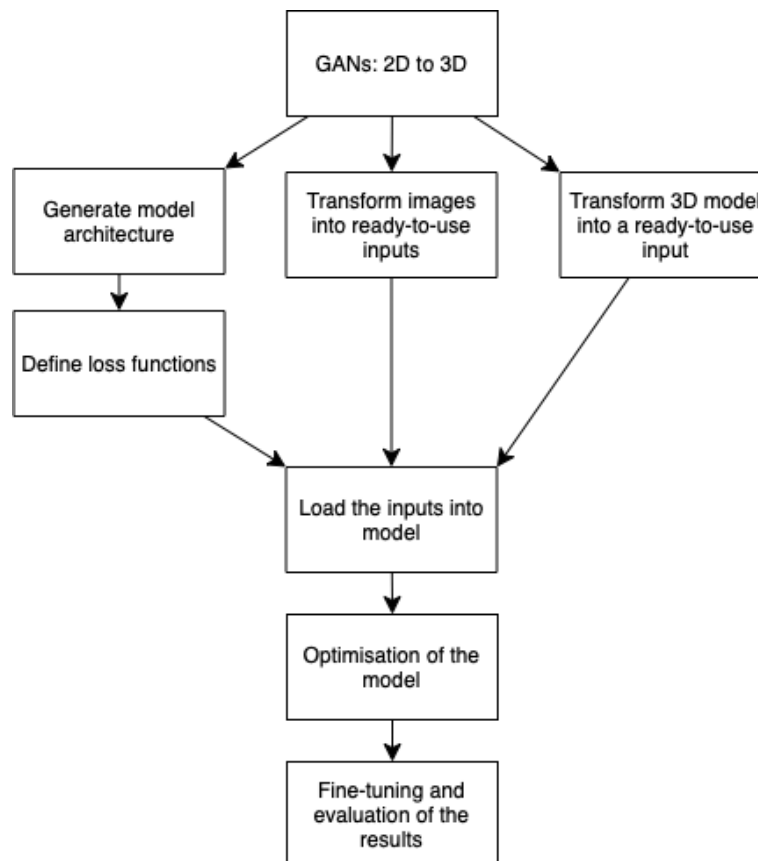


Figure 6. Study design of the 2D-to-3D approach.

Generative Adversarial Networks are a part of unsupervised Machine Learning algorithms, and the workflow consists of two neural networks contesting with each other in a

zero-sum game framework. They were first introduced by I. Goodfellow et al, 2014^{xv}. The two networks are the following:

1. **Generator.** It generates new data instances, taking random noise as input and producing an output, e.g., an image.
2. **Discriminator.** It evaluates the data instances. It will take both real inputs and fake inputs (by the Generator) and will predict the probability of the instance being real.

The algorithm will train the generator first, which tries to produce data like the real data as closely as possible, to ‘fool’ the discriminator. The generated samples can be of low quality in the first iterations. Then, the discriminator will be trained, based on its performance when distinguishing between the real and fake data produced by the generator.

The training process will go on until the discriminator cannot tell between the real and fake data anymore, therefore $D(G(z)) = 0.5$ for all z , meaning that the output from the generator is as close as it can get to the real data.

Following this algorithm and implementing it into the project, one can expect an experiment, focused on multiple parts of the research, e.g., implementing neural style transfer for 2D images, applying style to 3D models, and working with a depth-aware algorithm for GANs.

Neural Style Transfer Algorithm

Neural Style Transfer is a technique that was first introduced by L. Gatys et al., in 2015. Based on their research, the ‘style’ comes from the design to capture texture information. This process relies on pre-trained convolutional neural networks, also called CNNs, to extract and manipulate the feature representation of images. This is done usually by using VGG-19, a CNN that is 19 layers deep and used for image classification, image recognition, and object detection tasks.

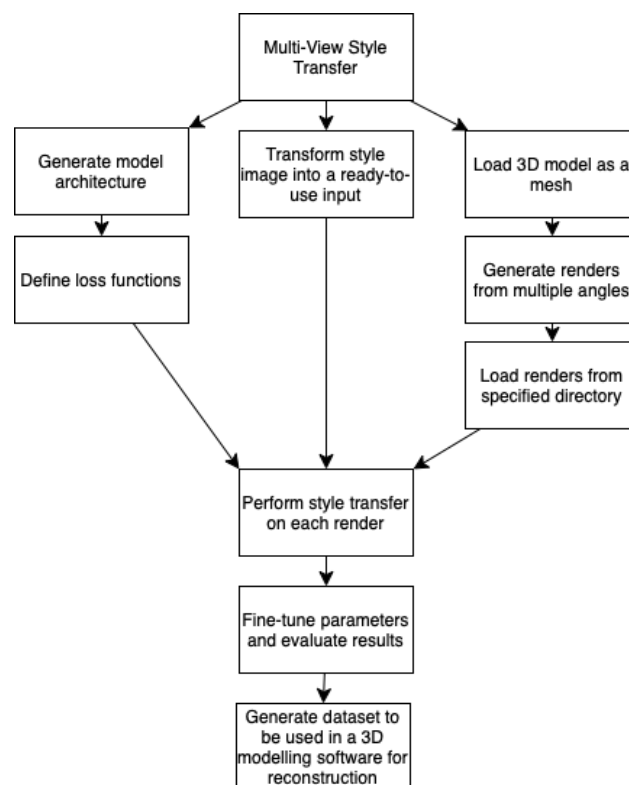


Figure 7. Study design of the Multi-view Style Transfer approach.

This algorithm consists of three main components, which together work on optimising a loss function: Content Loss, Style Loss, and Total Variation Loss.

1. Content Loss

Content Loss ensures that the meaning and the arrangement of the content image are preserved in the output image. It is typically defined as the squared error between the feature representations of the content image and the generated image, and it is expressed as:

$$L_{content}(p, x, l) = \frac{1}{2} \sum_{i,j} (F_{ij}^l - P_{ij}^l)^2$$

where:

- F^l and P^l are the activations of the l -th layer of the CNN for the output and content images.
- i and j will go over the 3D feature map generated by the layer l .

2. Style Loss

Style Loss will measure the difference in texture and visual patterns between the style image and the output image. It uses a concept called the Gram matrix, which will calculate the correlations between the different filter responses. For each layer l , a Gram matrix will be computed by reshaping the feature maps into a matrix F , where each row represents a vectorized feature map. The Gram matrix then will be equal to the product of F and its transpose, and it is expressed as:

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l.$$

The style loss for a layer l is the mean squared error between the Gram matrices of the style and output images, expressed as:

$$L_{style}^l(s, x) = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l - A_{ij}^l)^2$$

where:

- A^l and G^l are the Gram matrices for the style and output images.
- N_l is the number of feature maps, and M_l is the size of each map in layer l .

The total style loss is the sum of the style losses across all layers taken into consideration, each weighted by a user-defined weight w_l , expressed as:

$$L_{style}(s, x) = \sum_l w_l L_{style}^l(s, x).$$

3. Total Variation Loss

For the consistent transfer of spatial continuity and noise reduction in the output image, total variation loss can be used, expressed as:

$$L_{tv}(x) = \sum_{i,j} \left((x_{i,j+1} - x_{i,j})^2 + (x_{i+1,j} - x_{i,j})^2 \right).$$

Based on these losses, a full objective function that will need minimising can be computed, and it is a weighted sum of the three loss components, expressed as:

$$L_{total}(p, s, x) = \alpha L_{content}(p, x) + \beta L_{style}(s, x) + \gamma L_{tv}(x).$$

where:

- α , β and γ are the weights dealing with the relative importance of content, style, and smoothness.

After calculating the losses and minimising the full objective function, optimisation will be performed. The loss function will be minimised using a gradient descent technique, one of the most common ones for optimisation being Adam. This will ensure the process finds a balance between maintaining the content features and characteristics and adding the artistic style.

This algorithm is adopted by most of the experiments described in this research. Certain parameters, such as the number of optimisations performed and the number of layers, will be changed to find the best possible style transfer between the images used. It is also important to mention that each image needed to be loaded using alpha channels for them to be used in the algorithm, to ensure features such as transparency and layer blending are correctly handled, but also to preserve the quality of the output image.

Section 4

2D-to-3D – Generative Adversarial Network model

The testing process started with creating a new project in Visual Studio Code, a new repository in GitHub, and working solely with Python as a programming language. Two datasets were used for the initial tests, namely '*Architectural Styles*'^{xvi} by Z. Xu and '*Houses3K*'^{xvii} by D. Peralta. One of the challenges that presented themselves was having both a 2D image and a 3D model as inputs, to perform style transferring from the image (which would be the architectural style) to the 3D model (the building).

As a first try, the code was split into the following parts:

a. Generator

This is a neural network module for generating the output. Unlike other Generative Adversarial Network Models, there is no need for a Discriminator, as there is no need to supervise the process, only to generate results. The module will have 3 linear layers, based on the inputs, outputs, and the combined result: *fc_image*, *fc_mesh*, *fc_combined*, and *fc_output*. This forward method will take the noise value set in the beginning, the image and mesh features as inputs, will apply linear transformations with ReLu activations, will concatenate the results, and will produce the output.

b. Loading Functions

This module has two functions, utilised by the other scripts as libraries. It is necessary to create both, as inputs with different extensions are needed for modelling:

- *Image Loading*

The process consists of resizing the image file, which will then be converted to a tensor, and then normalised. The image is returned afterwards with an added batch dimension, to be used in the testing process.

- *Model Loading*

This process will read the 3D model needed as input will be converted to a mesh will extract the vertices and faces from the mesh and will concatenate these into an additional array, to be used in the testing process.

c. Main script

The main script will handle all transformations. It will utilise the previously mentioned modules and load the inputs, will instantiate the Generator and will generate the 3D mesh to show the output. For the generation of the output mesh, the library used is *mayavi.lab*.

Additional notes based on the code include:

- The noise variable can be modified. Based on this, one can determine how complex the output needs to be.
- The extension needed for the 3D model is *.OBJ*. The conversion methods will only work with models with this extension.

At the end of this test, several **limitations** could be made:

- There was constantly an issue with the sizes of the inputs, which would not match. Based on this observation, an improvement would include a conversion for both inputs to a specified size.
- One cannot determine the depth of the style transfer. The assumption is that the image used as input will just be added to each surface of the mesh.
- Other libraries for handling the 3D model could be tested. *Mayavi.lab* is subject to setbacks, often throwing errors such as: “*Generated mesh data is empty.*”.

By looking at these observations, there was a clear shift that needed to be made from a Generative Adversarial Network model to a Neural Style Transfer model, which would focus on the 3D model’s features and characteristics and extract the patterns from the input images.

2D-to-3D – Neural Style Transfer model

For the second try of this experiment, the main model used was a Neural Style Transfer model from Tensorflow, adapted to the needs of this project. This was a novel approach to applying 2D artistic styles to 3D models, through a combination of traditional image processing and modern 3D convolutional neural networks.

The code consisted of four parts:

a. Style Content Model

This is a file made up of two classes and a function, all focusing on extracting style and content features from images and 3D models.

- A class was made for 2D images, using VGG-19 to extract style and content features from input images (the architectural style images) and format them to match the expected input dimensions of the pre-trained VGG-19 model.
- A secondary class was made for 3D models, which aimed to adapt the concept of style and content extraction to 3D data, reshaping and processing the input to fit the 2D VGG-19 input requirements. This has failed due to the 3D-to-2D conversion.
- An extra function was included, to construct a 3D CNN model with multiple convolutional and pooling layers, designed to handle voxelised 3D data for style transfer.

b. Loading Functions

This module consisted of the same function as for the previous test but included an extra function for converting a mesh model into a voxel representation, which can be used as input for 3D CNNs.

c. Utility Functions

This module contained functions supporting the neural network operations:

- A function for converting a TensorFlow tensor into a PIL image, adjusting colour scales and dimensions.
- A secondary function for computing the Gram matrix for the style transfer process.
- A third function for extracting specific layers from the pre-trained VGG-19 model, to be used for style and content feature extraction.

d. Main script

The main script orchestrated the experiment. It first processed the inputs, such as the style images and the 3D model, then defined specific layers of the VGG-19 model to represent the style and content features. Afterwards, the 3D model was converted into a voxel grid for the 3D CNN. The 3D CNN was then built, and content and style losses were computed using the features extracted by the 3D CNN. For the style transfer, a modified VGG-19 was loaded and an attempt to apply the style transfer algorithm to the 3D voxel data was executed.

At the end of this experiment, limitations included:

- Lack of appropriate 3D pre-trained models, due to VGG-19 not being suitable for 3D data.
- The style and content loss calculations used in style transfer were not translated correctly to 3D data, as they are specifically made for 2D images.

Therefore, a hybrid approach was implemented, to attempt to better align the capabilities of neural style transfer technologies with the requirements of 3D modelling.

Multi-View Style Transfer

The end experiment of this research included systematically applying architectural features and characteristics to multiple renders of a 3D model, attempting to create a stylised representation from different angles. This approach will assess how effective a technique like 2D style transfer can be in a 3D context, mostly when applying it to multiple views of the model. The data used included the style images, namely '*Architectural Styles*'^{xviii} by Z. Xu, and a Bamboo House model in an .OBJ format.

There were multiple tries carried out. Firstly, a simple box was modelled, to identify how renders would look like when done in a script format. Afterwards, simple style transferring was done using a box model render and a style image with baroque architecture, namely the architecture of Santa Maria di Nazareth, in Venice, depicted in Figure 17. The output can be seen in Figure 8. Judging by this, several limitations included the difficulty to interpret the content of the image, and the inability to understand the depth and features of the initial model.

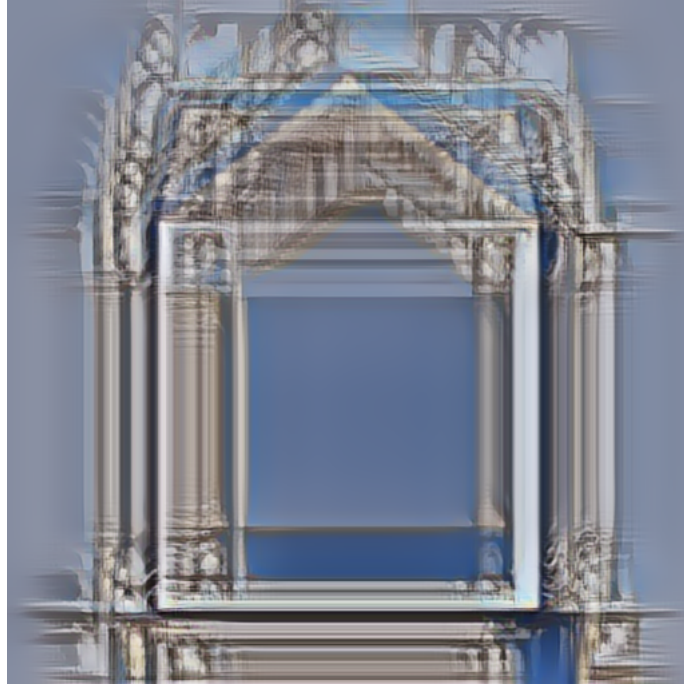


Figure 8. Output of the box model with a Baroque style.

Based on this, a new model containing a bamboo house was used as an input, pictured in Figure 9. The original test had the same baroque image as the style image, and the results can be seen in Figure 10. Some of the background needed to be cut to have more accuracy in the output, but also try different styles on the same model. Throughout working on this process, several parameters, such as the number of optimisation loops, number of epochs used per optimisation, angles, heights, and background lighting used in the rendering process, and layers used for the style transfer, kept being modified, to ensure the best possible transfer of the architectural style on the model was carried out.



Figure 9. Rendered image of the bamboo house model.

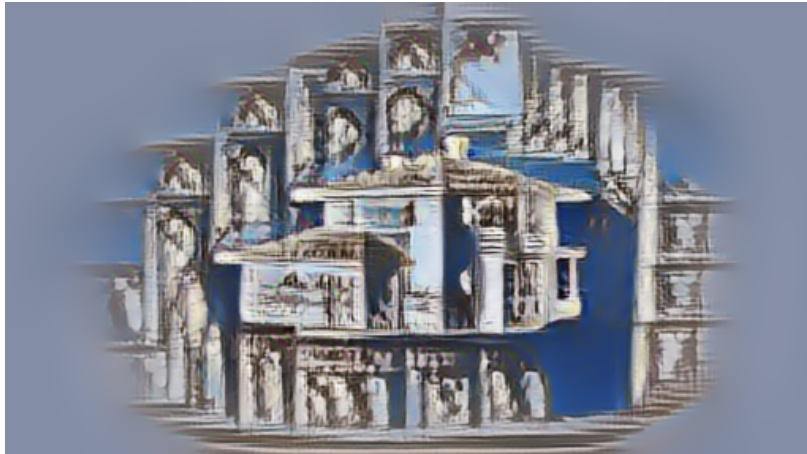


Figure 10. Output image of the model and a Baroque style.



Figure 11. Input image of a Tudor Revival architectural style.



Figure 12. Output image of the model and a Gothic style.

Another result of an experiment worth mentioning is the Tudor Revival style transfer on the model. The input image can be seen in Figure 11. The output, seen in Figure 12, starts having a blue and green background, both elements being visible in the input image, particularly the greenery and the sky. As such, it was necessary to eliminate the background and fully focus on the façade itself, rather than on the full picture from the dataset, as the details could disturb the overall features transferred to the model.

After multiple tries with various input images and the same model, a method having 5 epochs, 50 steps per epoch in the optimisation, the light intensity of 0.3 with soft, ambient light and 7 angles with an eye-level height for the rendering was used, and the background was removed. These parameters performed the best on this type of style transfer, having the finest output images. Results can be seen in Figure 13, and the style image in Figure 14.



Figure 13. Output image of the model and an Edwardian style.



Figure 14. Edwardian style input image.

The code consisted of three main parts:

a. Style Transfer Model

This module handled the core functionality of style transfer.

- Setup: It first defined a model that uses pre-trained VGG-19 layers to extract style and content features from images.
- Style Transfer: Through a function, it performed the style transfer process, while adjusting images for processing, running optimisation to minimise style and content loss, and merging style elements from the style image with content features from the content image.
- Loss Calculations: Included some functions that calculated the style, content, and total variation loss for the optimisation process.
- Utility Functions: Included functions to load content and style images through proper formatting and processing preparation.

b. Image Functions

This module contained multiple functions which supported image handling and manipulation.

- A function for removing the background from images and converting to a PNG format, helping the style transfer work on the content, rather than on the background.
- Functions to load images while maintaining aspect ratio and supporting conversions.
- Handled the setup and execution of the 3D model rendering through VTK, including setting camera angles, lighting, and height.

c. Main script

The main script carried out the operations in order:

- Setup: Imported the necessary libraries and defined the paths for the inputs and the output directories.
- Loading: Worked with various style images with architectural styles, such as Gothic, Edwardian and Baroque.
- Output Handling: Created directories for storing the output images, following a naming convention: date and the architectural style used.
- Rendering: Utilised the previously mentioned function for rendering the 3D model from multiple angles, and each image is saved as an image file.
- Pre-processing: The background from the rendered images is removed, for better focus during style transfer.

- Style Transfer: Performed the algorithm for each processed image using a specified style image, and all images are saved in the specified output directory.

After obtaining a dataset formed of the stylised renders of the 3D model, several ways were tried to attempt reconstruction of the model. The first one was Agisoft Metashape, a software used for photogrammetry. Essentially, it takes a dataset of photographs of the same object, but from different angles, and attempts to create a point cloud of the object being photographed. The photos of both the renders and the outputs were added, to try and model the original model and then the output one. Unfortunately, Agisoft Metashape works with a target system and real pictures, therefore it was looking for certain artificial targets in the photographs, which could not be found, due to the images being generated.

The second software that was tested was Adobe 3D Substance Painter, which works with a 3D model and different textures that can be added to the outside structure. The output images were uploaded to the software, along with the 3D model. The images were firstly converted to textures, and then the appropriate texture was added to the model, the result visible in Figure 15. The walls appear to be pixelated and the roof was left with its original texture.

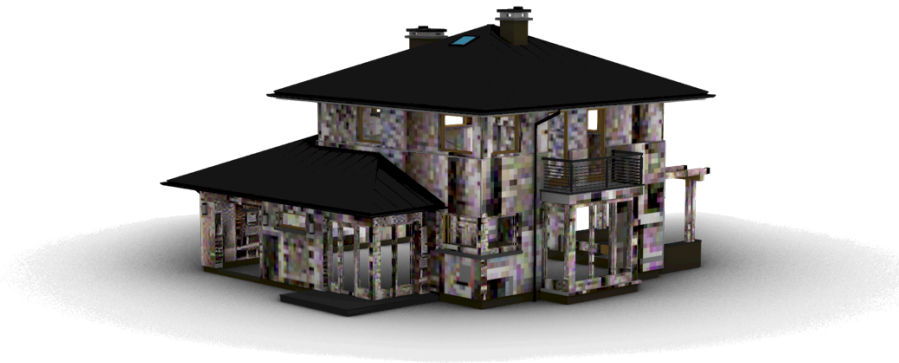


Figure 15. Model output after applying the results.

After this test, several observations could be made:

- The quality of the output images needs to be reassessed. To attempt reconstruction of the 3D model, these images need to be of an acceptable quality.

- The algorithm is still in its early days, to try to use it in the Built Environment. Some features and characteristics from the input image can be seen in the output, but architects cannot rely yet on these methods when designing.
- There is a need to identify and extract the features from both the input image and the 3D model. The same pattern is being transferred to both walls and roof. Therefore, for better accuracy, the transfer could be done separately, ultimately combining the results of each part of the 3D model.
- Software such as Agisoft Metashape cannot be used yet when attempting to reconstruct a 3D model from generated images, as this still relies on real photographs and artificial targets.

Further steps for this type of testing would essentially include using renderings from multiple angles for an easier reconstruction of the model, better quality for the output images, feature identification and extraction for a better understanding of the model and an easier transfer of the architectural characteristics.

Additional Testing

2D-to-2D Style Transfer

Other tests that were carried out include neural style transferring, from 2D to 2D, outlined by L. Gatys et al, 2015^{xix}. The code is primarily based on Tensorflow and takes two images, a content image and a style reference image and combines the two, such that the output has the same style as the reference. The images used for this test can be seen in Figure 16 and Figure 17. The process included working with the same dimensions, such that the images match, and making layers for the models so that one can get the content and the style representations of the image. The first few layers of the neural network contain low-level features, like edges and textures, while the last few layers contain high-level features, such as the object's parts.



Figure 16. Image of a New York facade.



Figure 17. Image of a Baroque Architectural Style - Santa Maria di Nazareth, Venice.

The model is then built in a similar way to the first test, and the content of an image is represented by the values of the intermediate feature maps, calculated through a Gram matrix. The style and content are then extracted, to be used in the style transfer algorithm. For the errors, the algorithm uses gradient descent and total variation loss. These are fed back into the model, using backpropagation, essentially running as a feedback model.

As a result, one can see Figure 18. There are clear features of the content image, but the model is trying to copy the architecture of the style reference image and adapt it to the input.

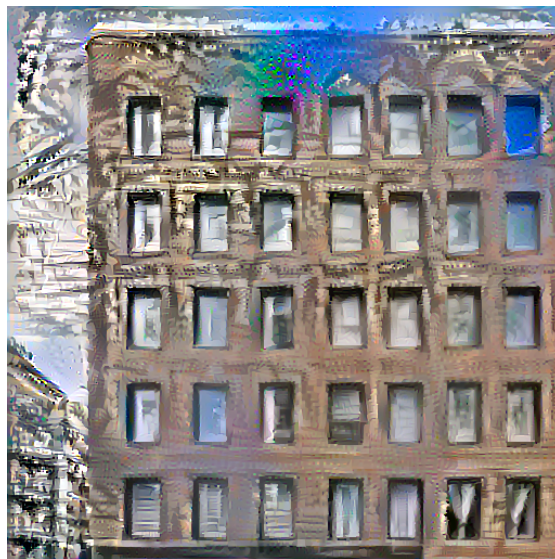


Figure 18. Output image from Neural Style Transfer.

MiDaS – Multi-Scale in Depth and Semantics

A software that had a lot of potential and was included in a test utilises a depth algorithm, namely MiDaS, which stands for Multi-scale in Depth and Semantics^{xx}. The goal of the algorithm is to determine the distance of each point in an image from the camera. This would be particularly useful for the research, as it would better understand where to place the style of an image on a 3D model.

MiDaS extracts features from an input image at multiple scales, therefore analysing the image at different resolutions. It also incorporates semantic information into its depth estimation process, through understanding the context and content of the image, leading to more accurate depth predictions. This algorithm works differently from others of the same type through its training process – it was trained on a diverse set of data sources, including indoor and outdoor scenes, making the model versatile in different applications. The result of the algorithm is a depth map, which is a grayscale image where each pixel's intensity represents its estimated distance from the camera. For testing purposes, Figure 17 was used to understand the depth map of the image, and the result can be seen in Figure 19.

This test could essentially be used in further research by combining this method with the neural style transfer algorithm, leading to applying it to a 3D model, possibly in a Multi-view Style Transfer (generating multiple 2D images from a 3D model and using them as a separate dataset in the model).

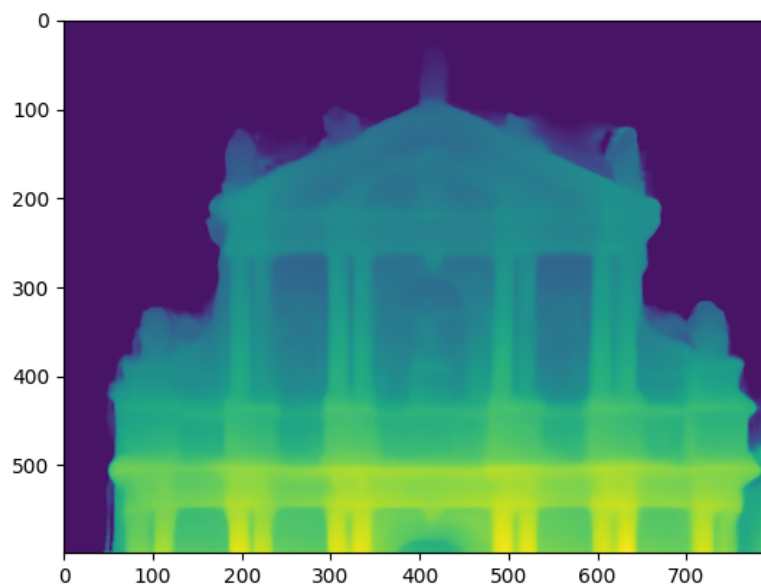


Figure 19. Depth map for Figure 14, using MiDaS.

Section 5

Discussion

For this research, the starting point was the literature review – seeing what the new developments in the field were, what was missing and how one could fill in the missing gaps. The performance of Neural Networks in the Built Environment is still at the beginning, nevertheless showing great promise. Through I. Goodfellow et al, 2014^{xxi}, one could understand how the models worked and therefore start applying them in the field, with many more coming afterwards – L. Gatys et al, 2015^{xxii}, showed this performance in their *A Neural Algorithm of Artistic Style*, which has also influenced many other papers specific to Architecture, e.g., H. Zhang et al, 2019^{xxiii} and 2020^{xxiv}.

Based on the papers, it was clear that most of the work done in terms of Neural Style Transfer was on 2D images. Some work was done on 3D meshes, such as H. Kang et al, 2023^{xxv}, but it is still in an early stage of development. The research question, therefore, was: how could 2D architectural styles be applied to 3D models of structures using accessible technology and methodologies? This question guided the methodology, and a series of extensive tests were started. The tests were using Neural Network models, specifically Generative Adversarial Network models and Neural Style Transfer models. The principles of these are explained in the Methodology, and one can identify two ways in which this could go: having the 3D model converted into a mesh and used as input, to then be tested with a 2D image; or having a dataset of images taken of the 3D model and use them as 2D-to-2D with the style image. Additional tests included Neural Style Transfer from a 2D image of a Baroque architectural style to a 2D image of a façade, and depth map test on the same image of a Baroque architectural style, using MiDaS - Multi-scale in Depth and Semantics.

After performing the tests, key findings include:

- For this type of research, Generative Adversarial Network models do not fit the purpose as much as other neural network models, such as Convolutional Neural Networks. The GANs mostly focus on identifying the differences between generated images and real images, rather than just generating novel images with architectural features from another image.
- Using Neural Style Transfer models on a 3D model is a very novel approach, and there is not enough research done into it to fully understand how this algorithm might

work. Therefore, certain neural networks and packages that come with this technology might not translate well to 3D inputs, due to different spatial correlations in 3D space. For further research in this domain, integration of 3D texture information capture into existing neural networks working with 2D data, such as VGG-19, is essential to start transferring features from one image to a model.

- Neural Style Transfer does not fully capture the intricate details, characteristics, and patterns of an architectural style, to then translate to a 3D model. Features such as the roof, windows, and doors ended up having the same pattern that was added to the walls. This highlights the need for preliminary steps like feature identification and extraction to achieve a more precise match between input images and models, as well as deepen the comprehension of the output.
- Technologies such as MiDaS may help address challenges, such as feature identification and extraction, by streamlining them. Merging this feature into the existing Multi-View Style Transfer model developed for this research could potentially lead to better results and a more precise understanding of the spatial correlations, both for the input image and the 3D model, within the algorithm.

Conclusion

This research focused on understanding how existent technologies and methodologies could help 2D architectural styles be applied to 3D models of novel buildings. In this context, architectural styles referred to a series of characteristics and features found on a façade of a building in question, and the inputs included images of facades with a Baroque architectural style or an Edwardian one. Working on multiple tests with various models, such as GANs and NST models, but also learning about technologies such as MiDaS, several limitations have arisen, along with many key findings. Overall, the field is fairly at the beginning of its integration into the Built Environment, but the connection between machine learning and architecture will continue to grow in time, having substantial impacts and aiding the latter field tremendously.

Appendix



Figure 20. Output image of the model with a Bauhaus style, 10 epochs/10 steps.



Figure 21. Output image of the model with a Gothic style, 10 epochs/5 steps.

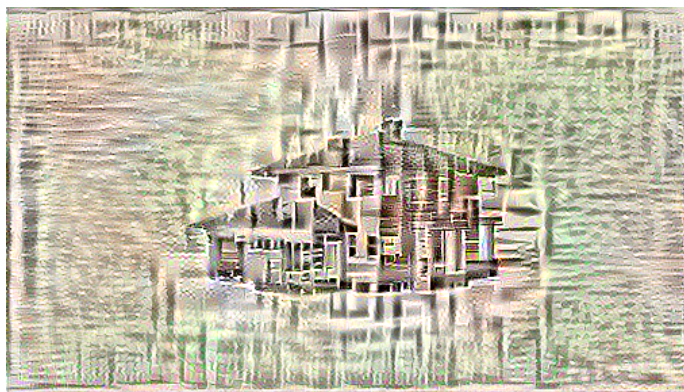
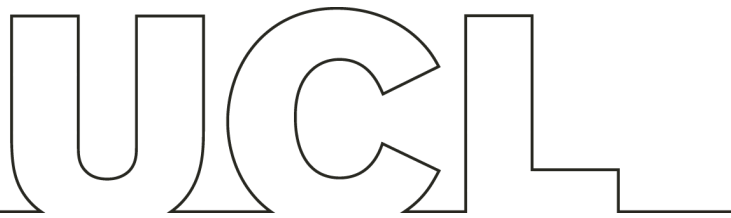


Figure 22. Output image of the model with an Edwardian style, 5 epochs/5 steps.

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MEng EAD Dissertation Module Research Ethics, Data Protection & Risk Check Part A: Declaration of Review Stream Applicable to the Research

This document is for MEng EAD students to use to determine which ethics stream is applicable to their Dissertation research. It was created by the BSEER Research Ethics Committee. It comprises five steps:

- **ALL STUDENTS TO COMPLETE...**
Step A1 – Does the research require a *Risk Assessment*?
Step A2 – Does the research require *External* research ethics approval?
- **Where external ethics approval is not required, students complete...**
Step A3 – Is the research *Exempt* from the need for ethics approval?
- **Where the research is not exempt from the need for ethics approval, students complete...**
Step A4 – Does the research require *High Risk* ethics approval?
- **Where the research is not exempt from the need for ethics approval, but does *not* require high risk ethics approval, students complete...**
Step A5 – Does the research require:
 - Low risk ethics approval for *questions-based methods* – from MEng EAD .
 - Low risk ethics approval for *monitoring-based methods* – from MEng EAD .
 - Low risk ethics approval for *other methods* – from BSEER.
- **ALL STUDENTS TO COMPLETE...**
Step A6 – MEng EAD Dissertation Ethics *Declaration* where students and their supervisors declare
 - Whether or not the research requires a risk assessment, and
 - Which of the following ethics review streams applies to the Dissertation research:
 - External (to UCL) research ethics review [this outcome is unlikely].
 - Exempt from the need for research ethics approval.
 - High risk research ethics review from the UCL Research Ethics Committee [this outcome is unlikely].
 - Low risk research ethics review for questions-based methods – from MEng EAD Ethics PGTA.
 - Low risk research ethics review for monitoring-based methods – from MEng EAD Ethics PGTA.
 - Low risk research ethics review for other methods – from IEDE Ethics Lead (if applicable, prior Data Protection registration required).

The MEng EAD Dissertation Ethics *Declaration* is submitted to the BSEER IEDE Ethical committee lead as per their instructions. The Ethics PGTA will return the review form to the student, if applicable. The *Declaration* and the review form (if applicable) are included as a Dissertation Appendix. The first supervisor needs to approve the submission of the *Declaration*.

Step A1 – Does the research require a *Risk Assessment*?

UCL has a duty of care to students under the Health and Safety at Work Act.

MEng EAD Students: If you are unsure about what to answer, consult your Supervisor.

Will you conduct any of this research:	YES	NO
Alone in a non-public place (e.g. dwellings other than those you usually use, workplaces with very few workers present, etc.)?	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Alone in a public place with few other people present (e.g. quiet park/street)?	<input type="checkbox"/>	<input checked="" type="checkbox"/>
In an area where the research topic might be considered sensitive?	<input type="checkbox"/>	<input checked="" type="checkbox"/>
In a laboratory at UCL?	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Overseas in an area where the UK Foreign and Commonwealth Office (FCO) advises against travel (amber / red on the FCO map of that country)? Note that familiarity with that overseas area is irrelevant to this answer at this stage (see below).	<input type="checkbox"/>	<input checked="" type="checkbox"/>

If you ticked YES to ANY of the above, you must undertake a risk assessment with your supervisor.

Your supervisor is responsible for ensuring that any risk assessment necessary for your research is undertaken and completed appropriately. If you have not already done so, complete the relevant Department's Risk Assessment template under the close supervision of your supervisor. Examples of a Fieldwork Risk Assessment template and instructions for completing it are available here, courtesy of the Department of Geography:

<https://www.geog.ucl.ac.uk/resources/safety/risk-assessment>.

ALL Students: Proceed to Step A2 – Does the research require external ethics committee approval?

Step A2 – Does the research require *external* ethics committee approval?

MEng EAD Students: If you are unsure about what to answer, consult your Supervisor.

	YES	NO
<p>1. Is your research social care research funded by the Department of Health? If you ticked YES, you require ethics approval from their authorised ethics committee.</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>2. Is your research funded, sponsored or undertaken by the Ministry of Defence? If you ticked YES, you require ethics approval from their authorised ethics committee.</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>3. Does the study involve participants lacking the capacity to give informed consent? A person lacks the capacity to give informed consent if at the time when consent is sought they are unable to make a decision for themselves in relation to the matter (i.e. deciding whether to participate) because of an impairment of, or a disturbance in the functioning of, the mind or brain. A person is unable to make a decision for themselves if they are unable:</p> <ul style="list-style-type: none"> a) to understand the information relevant to the decision, b) to retain that information, c) to use or weigh that information as part of the process of making the decision, or d) to communicate their decision (by talking, using sign language or any other means). <p>If you ticked YES, you require ethics approval from a research ethics committee falling within the UK Health Departments' Research Ethics Service (HRA). UCL committees cannot ethically review research involving participants who fall under the Mental Capacity Act 2005. When unsure please refer to the Mental Capacity Act 2005:</p> <ul style="list-style-type: none"> • People who lack capacity http://www.legislation.gov.uk/ukpga/2005/9/section/2 • Research http://www.legislation.gov.uk/ukpga/2005/9/part/1/crossheading/research 	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>4. Does your research involve any of the following:</p> <ul style="list-style-type: none"> • NHS patients and carers • Invasive research involving prisoners • Clinical Trial of an Investigational Medicinal Product • Human tissue requiring ethics approval from 'approved' ethics committee (Human Tissue Act 2004) <p>When unsure please refer to the HRA checklist and the decision tool.</p> <p>If you ticked YES, you require ethics approval through NHS Research Ethics Review (NRES).</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>

If your research DOES require external ethics approval, you must secure this from the relevant authorized ethics committee before data collection starts. Proceed to Step A6 – MEng EAD *Dissertation Ethics Declaration*.

If your research does NOT require external ethics approval, proceed to Step A3 – *Is the research exempt from the need for ethics approval?* (next page).

Step A3 – Is the research *exempt* from the need for ethics approval?

MEng EAD Students: If you are unsure about what to answer, consult your Supervisor.

Research that is not exempt and requires ethics approval	YES	NO
<p>1a. Will your research collect / use / store / process personal data?</p> <p>The legal definition of Personal Data is any information relating to an identifiable person who could directly or <i>indirectly</i> be identified from that information. It includes Personal Data that you are collecting simply to contact your participants. It is data that a motivated intruder or analyst (including you) <i>could</i> use to identify someone. This includes if someone could potentially identify individuals from an interview transcript, or from a subsequent report. Examples include:</p> <ul style="list-style-type: none"> • Name (can be sufficient to ID an individual; usually sufficient if combined with other information) • Email address / Phone number • Home address / Postcode • Photo / Audio / Video → can reveal ID if accessed by someone able to digitally enhance • Location data? EG taxi fleet location data can be processed to reveal identifiable information on individuals • Online identifiers (including IP addresses) • Data derived from electronic sensors or digital 'tracking' tools • Combinations of data that may reveal identifiable data (e.g. Employer + Job Title) 	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>1b. Will your research involve gatekeepers, human participants, or observing humans?</p> <p>All research involving human participants and/or their data requires ethics approval. Gatekeepers are people you involve in your project and seek permissions from (e.g., access to facilities, equipment installation, etc.)</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>1c. Will your research potentially raise other ethics issues?</p> <p>Research that does not involve human participants and/or their data <i>may still raise other ethics issues</i> that require consideration. Below are some examples that will require ethics approval (this list is not exhaustive):</p> <ul style="list-style-type: none"> • research on terrorism / extreme violence • research on pornography • environmental studies that have the potential to impact on or change the environment • archaeological excavations in disputed territories • studies involving access to sacred sites or the analysis of sacred cultural objects where access is restricted or where there are particular modern sensitivities or issues • access to indigenous communities that have come to insist upon prior permission gained from official or informal indigenous bodies • interpretations of publicly available data that make sensitive or personal claims about individuals. EG analysing speeches and concluding that the language used indicates dementia onset or autistic features 	<input type="checkbox"/>	<input checked="" type="checkbox"/>

If you ticked YES to ANY of the above, your research IS NOT EXEMPT from the need for ethics approval. Proceed to Question 2, below.

If you ticked NO to ALL of the above, your research IS EXEMPT from the need for ethics approval. Proceed to Step A6 – MEng EAD *Dissertation Ethics Declaration*.

Additional research that is exempt from the need for ethics approval	YES	NO
<p>2. Is all of your research literary or artistic criticism, or reviews of professional and other publicly-affirmed opinions?</p> <p>If you ticked YES, your research IS EXEMPT from the need for ethics approval. Proceed to Step A6 – <i>MEng EAD Dissertation Ethics Declaration</i>.</p> <p>If you ticked NO, your research IS NOT exempt from the need for ethics approval. Proceed to Step A4 – <i>Does the research require High Risk ethics approval?</i></p>	<input checked="" type="checkbox"/>	<input type="checkbox"/>

Step A4 – Does the research require *High Risk* ethics approval?

MEng EAD Students: If you are unsure about what to answer, consult your Supervisor.

Vulnerability	YES	NO
<p>1. Will your research involve participants who are particularly vulnerable? For example individuals:</p> <ul style="list-style-type: none"> • with learning disabilities or a cognitive impairment (see note below) • with emotional and mental health problems (see note below) • who are highly dependent or in unequal positions such as those in care who are unlikely to comprehend the rationale of the research or who are at risk of being traumatised or physically debilitated by it. <p><i>A person will not be considered automatically vulnerable if, for example, they are illiterate or have dyslexia or OCD. A vulnerable participant is someone:</i></p> <ul style="list-style-type: none"> - who is, or may be, in need of community services due to age, illness or a mental or physical disability - who is, or may be, unable to take care of himself/herself, or unable to protect himself/herself against significant harm or exploitation. 	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>2. Will your research include participants who due to their personal circumstances are particularly vulnerable? This includes asylum seekers, people in care facilities, prison, young offenders, refugees (UK and elsewhere), victims of crime, those who have suffered a traumatic event.</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Perceived pressure to participate (power relationships)	YES	NO
<p>3. Will the project involve researching your own students/clients? If so, will the research collect personal data that would not otherwise be disclosed during normal relationships/business?</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Sensitive Topics	YES	NO
<p>4. Will the project cover topics and include the collection of data that would usually be considered as sensitive? For example:</p> <ul style="list-style-type: none"> • terrorism / extreme violence (including contact with terrorists, communities in which terrorists are thought to be based or very likely targets of terror), • pornography (to include pornographic materials or contact with persons and organisations that make these materials), • exploration of participants' experiences of violence, abuse or exploitation, • exploration of participants' illegal behaviour (to include direct contact with those persons knowingly engaged in illegal activities). 	<input type="checkbox"/>	<input checked="" type="checkbox"/>
<p>5. Will the project involve collecting data that, if disclosed outside of the research, foreseeably would place the participants at risk of criminal or civil liability or be damaging to participants' financial standing, employability, reputation or their ties with family or standing in the community?</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Risk of Disclosure	YES	NO
<p>6. Will your research involve a risk of disclosure? In the course of their research, colleagues will sometimes collect information or data that appears to disclose criminal or illegal activity. In some cases there could be a legal obligation to inform the authorities. However, even if there is no legal obligation to report an activity, researchers may still find themselves in possession of information about acts that could potentially harm the participants themselves, specific third parties or the general public. <i>Although it is generally the case that information should remain confidential there are limits to confidentiality and situations where confidentiality will need to be broken. You must consider beforehand whether the research involves an increased likelihood of a disclosure happening should a participant tell the researcher something that causes significant concern, or it could be something that is observed during fieldwork such as an illegal activity.</i></p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>

Consent, deception and covert methods	YES	NO
<p>7. Will your research involve an element of deception or covert methods* (observation or other data collection), whereby fully informed consent is not obtained, partial consent is sought or participants are included without their knowledge?</p> <p><i>*This means situations where it is not appropriate to inform participants either in full or at all about the study as it may either affect the behaviour of participants and/or make it impossible to collect the data.</i></p> <p><i>This does not include observation of individuals in public spaces.</i></p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Intrusive/Medical Interventions	YES	NO
<p>8. Will your research involve any of the following intrusive or medical interventions:</p> <ul style="list-style-type: none"> • taking blood samples • administering drugs or other medicinal products • a medical device • exposure to strong magnetic fields, including Magnetic Resonance Imaging (MRI) and Transcranial Magnetic Stimulation (TMS) • making electrical recordings from muscle (ECG, EMG) or brain (EEG) • use of non-ionising radiation • physically intrusive procedures such as biopsies • DNA / RNA / genetic analysis • samples from participants that could reveal an unknown medical condition 	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Risk of Harm to Participants	YES	NO
<p>9. Will your research present a significant risk of harm to the rights and wellbeing of participants; physical, emotional (i.e. distress or humiliation), psychological (i.e. stress or anxiety), reputational, legal or financial beyond the risks encountered in normal life?</p> <p>The answer in this section should be 'yes' where there is a risk of participants experiencing psychological stress, anxiety, humiliation, harm or negative consequences as a result of participation and where this risk is significantly greater than anticipated for the participant in their everyday life. For example, the discussion of sensitive topics such as child abuse, terrorism, pornography, eating disorders, suicidal thoughts or sexual or political behaviour, experiences of violence, abuse or exploitation. However, discussing such topics with professionals whose work is related to those areas, such as social workers or psychologists, may not involve an increased risk of them becoming distressed as the nature of their professional lives is that these topics are for them less sensitive than for most people.</p>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Risk of Harm to Researcher/s	YES	NO
<p>10. Will your research present a real and/or significant risk to a member of the research team? This includes but is not limited to:</p> <ul style="list-style-type: none"> • working in potentially unsafe environments (e.g. overseas research where the FCO has advised against all travel) • lone working such as at night in non-public places where there are other risk elements to consider (for example, the study may be looking at domestic abuse) • engaging with groups or behaviour that could result in harm <p>The Social Research Association highlights these potential risks to researchers:</p> <ul style="list-style-type: none"> • physical threat or abuse • psychological trauma, as a result of actual or threatened violence or the nature of what is disclosed during the interaction • being in a compromising situation, in which there might be accusations of improper behaviour • increased exposure to risks of everyday life and social interaction, such as road accidents and infectious illness • causing psychological or physical harm to others 	<input type="checkbox"/>	<input checked="" type="checkbox"/>

If you tick **YES** to **ANY** of the above questions, your research is deemed high risk and you require approval from the UCL Research Ethics Committee (see <https://wiki.ucl.ac.uk/display/BI/Ethics>). Proceed to Step A6 – MEng EAD *Dissertation Ethics Declaration*.

If you ticked **NO** to **ALL** of the above questions, your research is not deemed high risk. Proceed to Step A5 —*Check if MEng EAD or BSEER Low Risk Ethics Review*.

**Step A5 – Does the research require
MEng EAD Low Risk Ethics Review for *Questions-based methods*
OR
MEng EAD Low Risk Ethics Review for *Monitoring-based methods*
OR
BSEER Low Risk Ethics Review for *Other methods*?**

This step is for the use of MEng EAD Dissertation students who have confirmed that their research does not require approval from an external ethics committee (Step A2), that their research is not exempt from the need for ethics approval (Step A3), and that their research will not include any high-risk elements (Step A4). It will help students determine whether they may apply for research ethics approval to the BSEER IEDE Ethical committee, or whether they should submit a BSEER Low Risk Ethics application.

MEng EAD Students: If you are unsure about what to answer, consult your Supervisor.

<p>1. Will you use questions-based methods or monitoring-based methods for your Dissertation?</p> <p>1.1 Questions-based studies</p> <p>Interviews are question-and-answer sessions with mostly open answer response options. They can be verbal (e.g. face-to-face, phone, video-call) or written (e.g. email, chat) and with either individuals or groups. Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>Focus groups: where researchers facilitate discussion on a topic among a group of participants. Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>Social surveys / Questionnaires are highly structured questions with mostly closed answer response options. They can be verbally administered by the researcher (e.g. face-to-face, phone), or written self-completion (e.g. paper, online, via apps). Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p style="text-align: center;">OR</p> <p>1.2 Monitoring-based studies include instrumental measurements of environmental parameters (e.g., temperature, humidity, air quality, sound levels, light levels), and observation data (such as counting people in a space) in private (or privately managed) spaces. Equipment could either be mains operated or battery operated (provided that batteries are built-in and/or contained in the case of the device). Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>If you ticked YES to ANY of the 1.1 OR 1.2, proceed to Question 2. If you ticked YES to ANY of the 1.1 AND 1.2, submit a BSEER Low Risk Ethics application If you ticked NO to ALL of the above, submit a BSEER Low Risk Ethics application (https://wiki.ucl.ac.uk/display/BI/Ethics) and proceed to Step A6 – <i>MEng EAD Dissertation Ethics Declaration</i>.</p>
<p>2. OTHER THAN these interviews / focus groups / questionnaires, OR environmental monitoring, will the research involve other methods or other data from human participants?</p> <p>Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>If YES, submit a BSEER Low Risk Ethics application (https://wiki.ucl.ac.uk/display/BI/Ethics). Proceed to Step A6 – <i>MEng EAD Dissertation Ethics Declaration</i>. If NO, proceed to Question 3.</p>
<p>3. Will you collect or use personal data for your Dissertation?</p> <p>The legal definition of Personal Data is any information relating to an identifiable person who could directly or <i>indirectly</i> be identified from that information. It includes Personal Data that you are not using as research data – EG personal data you are collecting simply to contact participants. It is data that a motivated intruder or analyst (including you) <i>could</i> use to identify someone. This includes if someone could potentially identify individuals from an interview transcript, or from a subsequent report. Examples include:</p> <ul style="list-style-type: none"> • Name (can be sufficient to ID an individual; usually sufficient if combined with other information) • Email address / Phone number • Home address / Postcode • Photo / Audio / Video → can reveal ID if accessed by someone able to digitally enhance • Location data? EG taxi fleet location data can be processed to reveal identifiable information on individuals • Online identifiers (including IP addresses) • Data derived from electronic sensors or digital 'tracking' tools • Combinations of data that may reveal identifiable data (e.g. Employer + Job Title)

Yes No

If **YES**, go to Question 4.

If **NO**, submit an MEng EAD Ethics Assessment Part B.1 *Research Ethics Protocol & Application – Methods involving questions*. Proceed to Step A6 – *MEng EAD Dissertation Ethics Declaration*.

4. Why are you collecting this personal data?

- Just for the interviews / focus groups / questionnaires OR for the monitoring studies (e.g., to contact participants)
Submit an MEng EAD Ethics Assessment Part B.2 *Research Ethics Protocol & Application – Methods involving questions* OR an MEng EAD Ethics Assessment Part B *Research Ethics Protocol & Application – Methods involving built environment monitoring*, accordingly.
- For some other aspect of my Dissertation as well / instead.
Submit a BSEER Low Risk Ethics application (<https://wiki.ucl.ac.uk/display/BI/Ethics>).

Proceed to Step A6 – *MEng EAD Dissertation Ethics Declaration*.

Step A6 – EAD MEng Dissertation Ethics Declaration

Statement of Risk Assessment & Ethics Approval Requirements
<p>Student Candidate Number [FILL IN]: FCPC5 Student Name: [FILL IN]: Bianca Bodo Student UCL Email Address: [FILL IN]: bianca.bodo.19@ucl.ac.uk Supervisor Name: [FILL IN]: Yair Schwartz Supervisor UCL Email Address: [FILL IN]: yair.schwartz@ucl.ac.uk Dissertation Research Proposal [FILL IN]:</p> <ul style="list-style-type: none"> • Title / Topic: Working with Generative Adversarial Models to aid Built Environment decisions. • Research Question(s) / Aims & Objectives: The aim of this dissertation is to understand how the models specified above can be used in the built environment, particularly in heritage preservation. The objectives include: <ul style="list-style-type: none"> - Sampling datasets, including 3D datasets of relevant cities and architectural styles, but also generating own datasets through photogrammetry or other techniques. - Working with GANs and Diffusion models, such as Pix2Pix, Midjourney, and CycleGAN with already-available datasets. - Identify gaps and limitations in the research and understand the inputs for the models when training. - Produce results and acknowledge how this research is useful for the built environment. • Data & source (specify all data to be used; if none, explain why): available datasets on Kaggle, Google Datasets, AWS. Sources found in the Bibliography. • Method(s) (specify all methods to be used): experimentation with GAN models (built by self), literary and artistic criticism.
<p>I have read and understood Step A1 ‘Does the research require a Risk Assessment?’ and: [DELETE ONE STATEMENT]:</p> <ul style="list-style-type: none"> • This planned research does NOT require a risk assessment.
<p>I have read and understood Step A2 ‘Does the research require External research ethics approval?’ and: [DELETE ONE STATEMENT]:</p> <ul style="list-style-type: none"> • This planned research does NOT require external ethics review.
<p>External ethics approval is <i>not required</i> and I have read and understood Step A3 ‘Is the research Exempt from the need for ethics approval?’ and: [DELETE ONE STATEMENT]:</p> <ul style="list-style-type: none"> • This planned research IS EXEMPT from the need for research ethics approval.
<p>[TO BE COMPLETED BY STUDENTS WHOSE RESEARCH IS NOT EXEMPT FROM THE NEED FOR ETHICS APPROVAL; IF EXEMPT, PLEASE DELET THIS WHOLE BOX]</p> <p>The research is <i>not exempt</i> from the need for ethics approval and I have read and understood Step A4 ‘Does the research require High Risk ethics approval?’ and: [DELETE ONE STATEMENT]:</p> <ul style="list-style-type: none"> • This planned research IS deemed high risk and approval from the UCL Research Ethics Committee will be secured before the research starts. • This planned research is NOT deemed high risk.
<p>[TO BE COMPLETED BY STUDENTS WHOSE RESEARCH IS NOT EXEMPT FROM THE NEED FOR ETHICS APPROVAL; IF EXEMPT, PLEASE DELET THIS WHOLE BOX]</p> <p>The research is <i>not exempt</i> from the need for ethics approval, does not require high risk ethics approval and: I have read and understood Step A5 ‘Does the research require EAD MEng low risk ethics review for questions-based methods OR BSEER low risk ethics review for other methods?’ and: [DELETE ONE STATEMENT]:</p> <ul style="list-style-type: none"> • This planned research requires EAD MEng Low Risk Ethics approval for questions-based methods and approval will be secured before data collection starts. • This planned research requires BSEER low risk ethics approval (for other methods), which will be secured before data collection starts.
<p>I confirm that:</p> <ul style="list-style-type: none"> • the information I have provided is accurate to the best of my knowledge. • if the answers to any of these questions changes, I will go through this protocol again.

NEXT STEPS:

- **STUDENT:** Copy the text of the *completed* statement above into an email and email it to your supervisor.
- **SUPERVISOR:** Reply to the email confirming your approval of the completed statement.
- **STUDENT:**
 - Submit this A6 Statement (matching the one approved by your supervisor) on Moodle as your *Dissertation Ethics Declaration*.

- Wait for the PGTA Ethics to send back comments or Reviewer form, if applicable.
- Include this A6 Statement as a Dissertation Appendix after you have **BLACKED OUT YOUR NAME & EMAIL ADDRESS** so the second marker can mark anonymously.