ArtiVisual: A Novel Type of Art
An Interactive User Environment for Generating New Art Pieces using a Generative Adversarial Network (GAN)

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ABSTRACT

In this paper a novel interactive user environment for image data exploration and understanding is proposed. The proposed approach combines a generative neural network with established state-of-the-art visualisation techniques to deepen the users understanding of not only the OmniArt dataset but also art in general. *ArtiVisual* is an interactive user environment for generating and analysing a set of art pieces. With ArtiVisual it is possible to generate images based on art movements or artist's styles via an interactive timeline. In addition, visualisations are presented that provide insight into the key features of existing images, present in OmniArt, together with generated images. The combination of a trained Generative Adversarial Network (GAN) and state-of-the-art visualisation techniques provides a rigid framework for thorough exploration and understanding of the image data.

1 INTRODUCTION

For thousands of years art has been a way to express the creative hunches of humankind. Evidence suggests that the first art piece ever found is 500,000 BP [1, 10]. Throughout the years many movements have been expressed and various artists have bequeathed to us marvellous art pieces, as for example Rembrandt van Rijn, who lived from 1606 to 1669. Though never a new art piece by Rembrandt will be created, Artificial Intelligence (AI) creates a possibility to generate new art pieces in the style of Rembrandt van Rijn.

In this paper a novel method is proposed to create art: ArtiVisual; an interactive user environment for generating new art pieces using a Generative Adversarial Network (GAN). This network will be trained on the OmniArt dataset [16], containing information on thousands of paintings and their artists. With the ArtiVisual application it is not only possible to generate images based on an artist, but also to generate images based on a specific artistic movement via an interactive timeline. In addition, visualisations are presented to provide insight into the dataset used. The interactive multiview presented in this paper was instantiated using the findings on good front-end design from the field of Information Visualisation, considering Gestalt principles, multiview rules, attention management, colour palette design, etc.

In this paper the following research question is answered: how can an interactive user environment for generating new art pieces be created that provides insight into the OmniArt dataset? In section 2 the related work on art visualisations and art in combination with AI will be discussed, as well as the state-of-the-art on GANs. In addition, we discuss the gaps currently present within these fields and how ArtiVisual attempts to bridge these. Section 3 describes the architecture design and approaches for the development of the application, technical considerations, and current prototype. Section 4 provides a testing bed and usability demonstration and the results from these experiments, i.e. the generated images. Lastly, in the discussion in section 5 the contribution, points of improvement, and further studies are mentioned after which the conclusions are presented.

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2 RELATED WORK

2.1 Art and Visualisation

Art – at least limited to the forms that are discussed within this paper – is highly visual in nature. However, even the visual arts are more than just some paint on a canvas. From the simplest sketch of a bowl of fruit to the most detailed depiction of some historical naval battle, each artwork represents the history of their creator, the other artworks that were inspired by them, and of the world they were created in. This is where the problem of displaying art pieces becomes apparent: visualising art is not about simply showing the piece, but about presenting it meaningfully within this context.

The obvious and most widespread method of displaying art pieces is through physical museums. Curation through museums utilises expertise from a wide range of domains and technological innovations to provide museum visitors with relevant information about their large collections [12]. Due to recent global developments, one particular technology, the virtual museum, has gained significant popularity among major museums [9]. These virtual museums often use 3D-graphics to represent the physical space of a museum in a digital space to be explored by users from their web browsers.

While museums often focus on prioritising some specific thematic subject, like a specific artist or movement, online search engines let users explore vast amounts of art images from arbitrary web queries. These search engines often combine the visual content of images as well as their context within their respective web pages to rank images based on their relevancy [6].

More recently, datasets such as OmniArt have inspired a wide range of methods for organising and visualising large collections of art. These methods often employ different types of machine learning to organise and explore these data in novel ways, such as exploration through colour [13] or visual sentiment and emotion [15].

2.2 Digital Art and Machine Learning

With the advent and wider availability of computers, many artists naturally jumped at the opportunity to express themselves in new and unique ways through this new technology. In the digital art resulting from this, a popular avenue of exploration is to train models how to generate novel works of art. Methods used to attain this goal classically employ a set of rules designed to either simulate the human cognition [2] or to imitate specific styles and/or artists [3]. Although these methods were able to generate imitations to an impressive degree, their ability to do so relied completely on representations and rules designed by the artist and could be difficult to generalise to other styles.

Recent developments in AI have enabled the use of deep generative networks: models that learn probability distributions over a dataset, which makes it possible to sample previously unseen data points that display the same characteristics as the training data. A notable early example of an application of these models is Neural Style Transfer [7], which separates the visual style of an image from its contents and applies it to another arbitrary image. Figure 1 shows how this method can be used to apply a painting's style to an image of a city, effectively creating a new painting in that artist's visual style.

More recently, high-resolution GANs (see section 2.3) have made it possible to not only emulate any artist's style, but also to generate completely new content and compositions. By exploring the latent space of these models, GANs can create works that have received ample critical acclaim and public attention in recent years [17].

Figure 1: Examples of Neural Style Transfer to create new "paintings" in the style of other artists [7].

2.3 Generative Adversarial Network (GAN)

A GAN is an algorithmic architecture that deploys two neural networks that strive to counteract each other. The aim is to generate new, synthetic instances of data that are indescribable from the original dataset [8]. The generative model captures the data distribution and a discriminative model estimates the probability that a sample came from the training data rather than the generator. The generator aims to maximise the probability of the discriminator being faulty [8]. Nvidia's styleGAN2 implementation [11] is able to produce adequate results using limited data. Where limited data often causes the discriminator to overfit, styleGAN2 implements an adaptive discriminator augmentation (ADA) mechanism that significantly stabilises training [11]. The ADA mechanism applies augmentations in an adaptive manner, by varying the magnitude of augmentation throughout the training process. Prior augmentation methods did not provide successful results as the GAN learned the augmentations themselves resulting in unrealistic images. Adaptive augmentation like styleGAN2 eliminates this problem. The styleGAN2-ADA combination can be used by researchers to build realistic big datasets out of a smaller set of images. For example, when developing an AI cancer detector that detects rare cancerous tumours a limited dataset can be enhanced with fake but realistic images of tumours generated by these models.

2.4 Gaps

The OmniArt dataset has been used for a wide range of visualisation applications. For example, the authors of the OmniArt dataset used a convolutional neural network (CNN) trained on a small subset of eyes from the paintings to extract a new dataset from OmniArt: OmniEyes [14]. This new dataset was used to visualise all sorts of information about eyes in artworks, e.g. eye colour and rotation. OmniArt, however, has yet never been used to generate new artworks. Furthermore, GANs have previously been successful in generating new artworks after training on existing artworks, while even being reported on being creative [4]. Information about generated artworks, however, was never visualised together with the artworks that were used to train the network itself. Such a visualisation could create a deeper understanding of these real artworks, e.g. what colours were dominant or even characteristic for a certain artist, and the dataset.

ArtiVisual bridges these gaps by offering an interactive user environment for generating new art. The application provides a platform for choosing the time period or artist to base the generated images on. Insights into the OmniArt dataset is provided by visualising how a generative neural network interprets different styles and genres. The generated images are visualised together with the images from the dataset to compare them, facilitating a deeper understanding of the dataset and its individual art pieces. ArtiVisual's novel method for visualising and interpreting image data will facilitate future research in exploring similar datasets with greater detail.

3 ArtiVisual

In the following sections the method for developing the ArtiVisual application is described, where each individual component and the reasoning behind them will be discussed. As an overview, figure 2 shows the architecture of the multiview application. In addition this chapter is structured according to the components in the architecture. The results following from this design will be discussed in section 5.

3.1 Architecture Design

3.1.1 Front-end

3.1.1.1 Interactive Timeline The first multiview component presented to the user is the interactive art timeline. The art timeline allows users to brush by drawing a selection box, filter by (de)selecting artists, or by adding or removing artists to/from the timeline altogether and selecting single artists and paintings. This also incorporates Shneiderman's mantra by first giving a large overview of c.a. 10 artists, giving the user the ability to zoom/brush and finally presenting the possibility to filter.

Selecting a painting or movement on the timeline can be done by clicking on a segment in the timeline. Hovering over a segment makes the segment perceptually pop out by increasing its size and showing a tool-tip with some information (name, artist, from and to year). Selecting a painting or time period allows the user to elaborate on the selection by getting the displayed painting (or a random one from that movement/time period), extra information, and a generated painting based on what was selected in the timeline (see also section 4).

3.1.1.2 Existing Art Pieces Carousel After selecting an artist, time period, or individual painting, the corresponding images are retrieved from the dataset and presented in an image carousel to give the user a quick overview of the general type of image, without using too much space. The carousels are shown prominently on the top of the screen to draw the users attention, as all of the other multiview components are based on the images shown in the carousels.

3.1.1.3 Generated Image After a selection from the user, multiple images are generated using the GAN based on the selection. One image is chosen to represent on the front-end. As with the existing art pieces carousels, the generated image is presented prominently on the top of the page so that the attention is drawn to this component.

3.1.1.4 Dominant Colour Pie-chart The dominant colour pie-chart presents the four dominant colours in the generated image. This was specifically chosen as the purpose of the chart is to convey

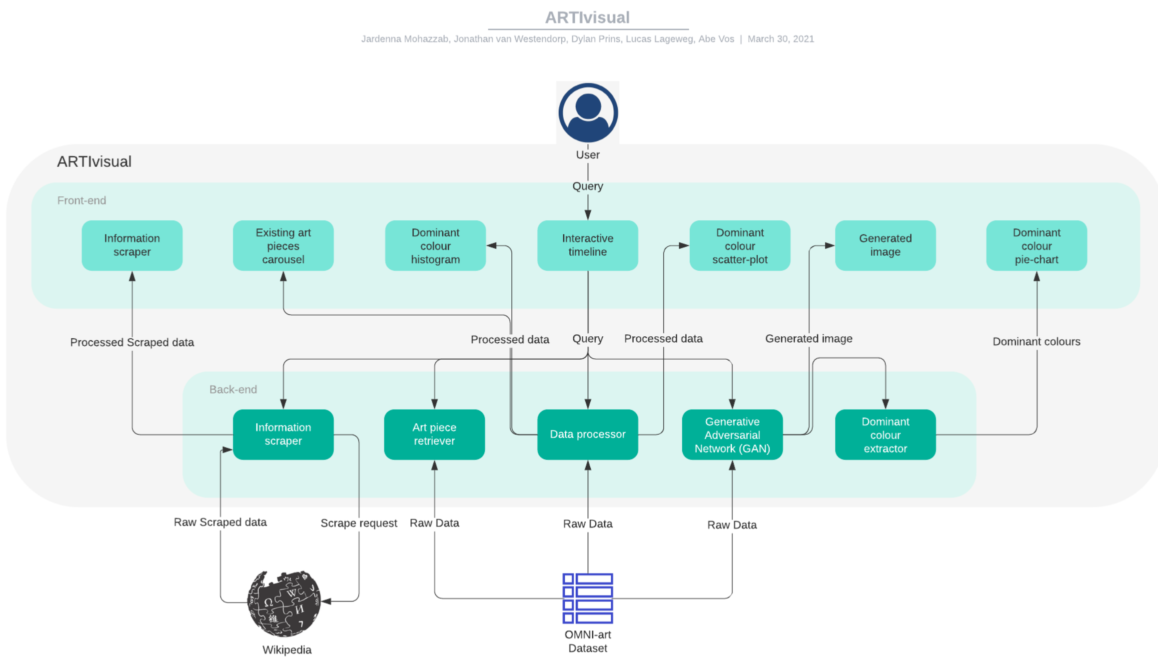

Figure 2: Architecture of ArtiVisual application

the dominance of colours, where exact percentages are not tremendously important but the user can easily compare the sizes of the different segments comprising the whole. As the colour dominance sums to a whole, the pie-chart is used instead of a bar-chart. The colours depicted in the pie-chart correspond to the dominant colours in the image.

3.1.1.5 Dominant Colour Scatter-plot

The scatter graph provides insight into the usage of colour by a specific artist or art movement/time period. For some artist or art movement, as selected by the user in the timeline, the hues of the dominant colour for each work within that selection are collected, similarly to the dominant colour pie-chart as described above. From this two representations are generated, the first being a scatter-plot showing how colour use changes over time. Any trends within this visualisation are emphasised by a polynomial trend-line.

3.1.1.6 Dominant Colour Histogram

The colour use following from the selection as described above for the scatter-plot over the whole time range is summarised in a histogram. The bars of the histogram are positioned vertically to make them align to the hue values on the vertical axis of the scatter-plot, alleviating the user's cognitive load by making the two visualisations more straightforward to compare. Both graphs support displaying multiple artists or movements at a time, allowing for intuitive comparison between selections of the data.

3.1.1.7 Extra Information on the Selection

Extra information about the selected artist or time period is provided, retrieved from the first few lines of their corresponding Wikipedia page, to give some general information on the selected matter to the user.

3.1.2 Back-end

3.1.2.1 Data Processor

To pre-process the data for the graphs as described in the sections above the unknown artists and art pieces are removed from the dataset. To process the data for providing the training data for the GAN a loop is performed through the dataset with the existing art pieces and stored in a JSON structure. The StyleGAN uses this structure to reshape the images to 256 pixels and label them. For processing the artists, 26 prominent artists throughout the centuries were chosen and based on this groupings were made.

3.1.2.2 GAN

The Nvidia StyleGAN2-ADA PyTorch model has been trained using the pre-processed OmniArt dataset as described above. The model was trained using the conditional configuration such that afterwards new images can be generated based on the same input conditions enabling the user to generate new images (paintings) based on a single artist or movement, e.g. creating a new Van Gogh or Renaissance painting.

In order to use the OmniArt dataset a custom dataloader, which converts the paintings information like its century of creation to labels which can be fed to the GAN, had to be built. For specific movements the centuries were used as labels, mapping each century into a range between 0-21. For artists a simple mapping which maps a single unique integer to each artist was used. These integers can be used as labels which can be fed to the GAN.

Two model configurations were trained, one for the movements and one for the artists using the *"auto"* preset which automatically sets all hyperparameters based on the data fed to the network. All images were resized to a size of 256x256. The two trained GANs are loaded into memory at startup to ensure a fast experience. When an artist or time period is chosen using the interactive timeline, an image is generated based on a random or set seed. When needed, the back-end route can also be used to generate multiple images. Before the images are returned, they are converted from an array of Python Image Library (PIL) images to an array of base64 images, ensuring that the images can be sent to the front-end without storing them as temporary images files on the file system first, again improving performance.

3.1.2.3 Information Scraper

The information scraper component retrieves relevant information according to the selection made by the user on the interactive timeline. The scraper retrieves the first three lines off the corresponding Wikipedia page of the artist or movement and presents a few related terms mentioned on the Wikipedia page.

3.1.2.4 Art Piece Retriever The art piece retriever extracts the relevant art pieces from the dataset according to the selection made in the timeline. The in-memory pre-indexed dataset is filtered to retrieve the corresponding image URL. An artist's first 6 images are retrieved whereafter these art pieces are passed to the front-end component to represent the images in the carousel. This ensures that the speed and processing costs are kept to a minimum, but at the same time provide enough insight into the dataset and the genre in particular.

3.1.2.5 Dominant Colour Extractor The four dominant colours within a single image is visualised using the charts as described above. These colours are extracted from the image via k-means. A JSON structure encoding this distribution is passed to the front-end where the charts can represent these colours.

3.2 Technical Considerations and Design Choices

3.2.1 GAN

In order to correctly run the application a CUDA enabled Nvidia GPU is needed with at least 8GB of VRAM. This is mandatory to load the pre-trained models which enables the user to generate the new images.

3.2.2 Multiview

A multiview visualisation approach was chosen which shows multiple sub-windows within the main canvas. Each information representation is divided into components via cards, since each component adds individual information and enables the comparison of multiple components. Here, the Gestalt law of closure is applied since boxes create a frame of reference, i.e. object positions are judged relative to the enclosing frame. In addition, the multiview rule of decomposition applies which partitions complex data into multiple views to create manageable chunks and provide insight into the interaction over different dimensions. Lastly, the multiview rule of consistency is applied by using uniform cards and headers.

3.2.3 Rendering Components

In an early design the user had to wait before all processes were finished before all visualisation could be presented. Currently, the back-end pre-renders the data for the visualisations. This design choice was made to integrate websocket events [5] that return the data for individual components and process these separately which makes it possible to visualise less computationally intensive components earlier. This way the user can continue to study his or her selection within the visualisation while waiting for the other components to render. Motion is used in order for the users to take notice of newly rendered components. In addition to this, the spacing of the specific components was chosen carefully to contribute to the multiview rule of attention management which uses perceptual techniques to focus the user's attention on the right and most important view(s) at the right time. For example as described earlier, it is desirable to attract attention to the existing and generated art pieces as these drive the rest of the components and comparisons made by the user.

3.2.4 Automatic Scaling

Adaptive scaling and positioning is integrated in the applications, scaling and placing the components according to the screen size and making the visualisation accessible to use on any kind of device regardless of screen size.

3.2.5 Colour Palette

As for the colour palette design, the background colour of the interface is white, whereas the visualisations are colourful and standing out. This is purposely implemented based on the Gestalt law of figure and ground which states that the eye splits the visual elements into figure (the data visualisations) and ground (background). Though dependent on the number of artists present on the timeline, not more than 20 different colours are aimed to be used on the screen.

3.3 Current Prototype

The current prototype can be found on GitHub and is available as open-source. The tool is programmed in JavaScript, HTML, and CSS, Python and Node. To structure the front-end and create style components, Vue.js is used. Express and Node.js are used to manage the back-end and communicate to the server. In section 4.1 a use case will be demonstrated and a walk-through will be described where each component is presented. In figure 3 and 5 the front-end of the current prototype can be seen.

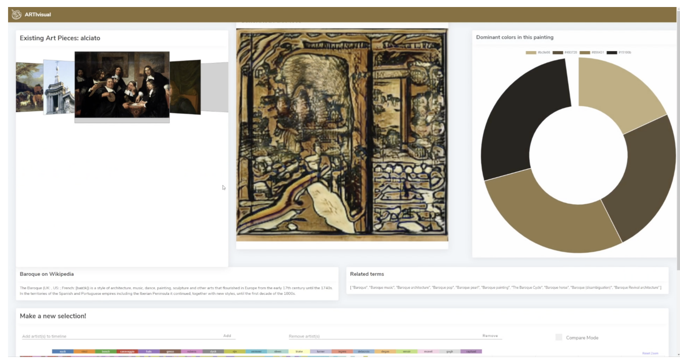

Figure 3: Front-end results when selecting the genre Baroque.

4 Software Demonstration and Validation

This section provides a usability demonstration of how the ArtiVisual environment can be used and describes a walk-through of the user experience. Section 4.1 presents a demonstration where a user wants to generate images in the style of Rembrandt. Section 4.2 states a testbed where images are generated based on the movement Baroque with the dedicated time period. Lastly, in section 4.3 the testbed for the compare page is proposed. The generated results will be presented in section 5. To demonstrate the user-experience a testing bed is proposed. There are three experiments that are executed using the ArtiVisual application.

4.1 Generate Art Piece Based on Artist

Firstly, when a user wants to generate images in the style of Rembrandt, it can be achieved by first selecting the artist on the initial page frame (see figure 3). For this experiment all years are selected. Afterwards the page is presented with the generated image and other information, including dominant colours of the image and information on the artist. In addition, the dominant colours used by Rembrandt are presented where also other artists and movements can be selected. The results of this experiment can be found in section 5.1.

4.2 Generate Art Piece Based on Movement

For the second experiment an image is generated based on movement. On the interactive timeline the movement Baroque is selected, after which the generated images are presented. To compare the dominant colours of the movement Baroque to other movements, the latter can be selected via the drop-down menu. The results of this experiment can be found in Appendix A.

(a) 2nd century - seed=13
(b) 2nd century - seed=27
(c) 12th century - seed=13
(d) 12th century - seed=27
(e) 16th century - seed=13
(f) 16th century - seed=27
(g) 21st century - seed=13
(h) 21st century - seed=27

Figure 4: Samples from the GAN Conditionally Trained on Centuries

(a) Vermeer - seed=0
(b) Vermeer - seed=9
(c) Van Gogh - seed=0
(d) Van Gogh - seed=9
(e) Picasso - seed=0
(f) Picasso - seed=9
(g) Warhol - seed=0
(h) Warhol - seed=9

Figure 5: Samples from the GAN Conditionally Trained on Artists

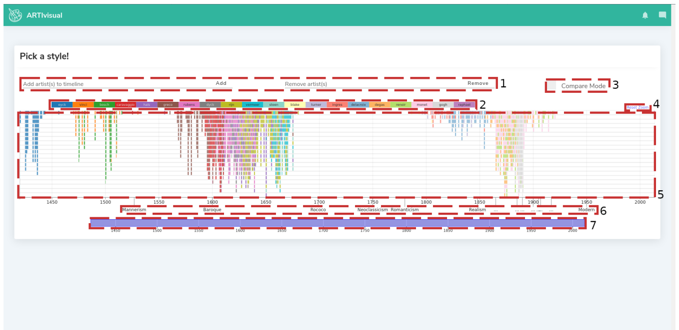

Figure 6: Overview of the timeline before a selection has been made. Interactive items that influence the selection are highlighted in red.

4.3 Compare Artists

For the last experiment the results of two artists are compared using the compare mode of the application. First, the box is checked to enable the compare mode. Secondly, the two artists Rembrandt and Monet are chosen in the interactive timeline whereafter the results are presented and the artists can be compared. The results of this experiment can be found in Appendix B.

5 Results

5.1 Front-end

The different multiview components as they are visible within ArtiVisual when making the selection for a single artists (or movement) are shown in figures 7, 8 and 10 to 13. The specific data that are visualised here are based on a selection of the artist Rembrandt van Rijn as described in section 4.

Figure 11 shows a man's portrait in a painting-style the model understands to be that of the artist. The pie-chart in figure 12 gives a quick overview of the colour palette in this generated image. A quick visual inspection also shows that the colour usage strongly corresponds to that of the real paintings shown in figure 10 and the usage of washed-out brown colours with a dark background is indeed very typical for Van Rijn's portraits.

The graph in figure 13 shows Van Rijn's use of colour within the context of his whole portfolio. Specifically, we can see that the artist seemed to prefer lower hue values – corresponding to warm colours like red, orange, and brown – although the trend-line suggests the average colour usage shifted towards cooler hues later on in his life. The histogram in figure 14 corroborates this observation by showing the density of dominant colours over Van Rijn's works. These two observations are easily linked in ArtiVisual, due to the histogram being plotted vertically making its vertical axis align to that of the scatter-plot.

Figures 9, 16 and 17 show the changed components for whenever the compare mode is selected and an artist selection is made by the user. The individual multiview components are identical as depicted in the single artists selection results. However, in compare mode the existing image carousel, generated images, dominant colour pie-charts, and extra information text boxes are put side-by-side for each of the artists in question.

5.2 GAN

As discussed earlier, two models were trained using the GAN. The first model tries to capture style based on century labels. The second model tries to capture characteristics of a selection of world renowned artists. Figures 4 and 5 show a selection of interesting generated images. For each artist and century, the images were generated based on the same starting noise (seed) so that they can be compared.

In figure 4, a gradual increase in image complexity can be seen. Seed 13 starts as something that can be interpreted as a physical object and changes to something more abstract, as the GAN probably sees relatively more abstract art as time progresses. Seed 27 clearly starts developing a face as time progresses. However, where figure 4d contains a face without any remarkable features apart from the whiteness, figure 4h can actually be considered very scary as it contains no eyes and something similar to a 'child' with the same features.

The GAN trained conditionally on artists (figure 5) contains images from two seeds *interpreted* by four different artists. Vermeer, mostly famous for painting people in daily life, e.g. "Het Melkmeisje", seems to generate a person, where the GAN conditioned on Van Gogh turns the seed into a landscape with trees. This landscape returns for Picasso and Warhol, however, clearly interpreted more abstractly. The generated images for seed 0 are more similar for every chosen artist. The main differences lie in shape and colour.

6 Evaluation and Cost Analysis

As ArtiVisual is an interactive multiview visualisation with multiple states, it evidently comes with some cognitive load to process for the user. Though user based evaluation on our visualisation has not been done, some insights can be gained on evaluating ArtiVisual based on the literature. As Van Wijk states: "Interaction should be used carefully and sparingly." [18]. Interaction is costly and rendering after mapping, and viewing it afterwards can take seconds. As the user is able to make multiple paintings, artist or time period selections during a session, this is the most costly part of our visualisation. To lower the interaction costs, as many actions automatically following an action from the user is applied. For example, if a user selects one or more artists, zooming is done automatically on the timeline to reflect the selection, and the statistics are rendered automatically using an animation to 'mask' the loading time. Next to that, in order to minimise the initial interaction costs a solid preset/pre-selection of artists throughout the centuries on the timeline to choose from was created.

Unfortunately, due to time constraints we did not have the opportunity to do an evaluation with users. This would be vital to really evaluate the cognitive load and interaction costs of the multiview and further optimise the multiview where needed.

7 Discussion

7.1 Contribution

The gaps in current related work reflect the novelty of this research. This research contributes by filling these gaps and provides a platform to generate these new art pieces in an interactive manner and provides insight in the data regarding these art pieces. This way users without any programming expertise can make use of this service.

7.2 Assessment

7.2.1 Generative Adversarial Network (GAN)

Gordon C. Aymar states: "The eyes are the place one looks for the most complete, reliable, and pertinent information about the subject."

And this shows in our results. The GAN finds it very difficult to generate realistic eyes. In fact, sometimes the GAN is not able to generate any eyes at all. Just showing black circles. Training for a longer period of time/using more powerful GPUs should eventually eliminate this problem. Using a more carefully hand-picked set could also help the GAN to generate images of higher realism. E.g. by using more faces in the dataset, which should provide less noise when trying to generate a portrait. This also shows for the images that are generated based on movement. Each century has various kinds of paintings like landscapes, portraits,

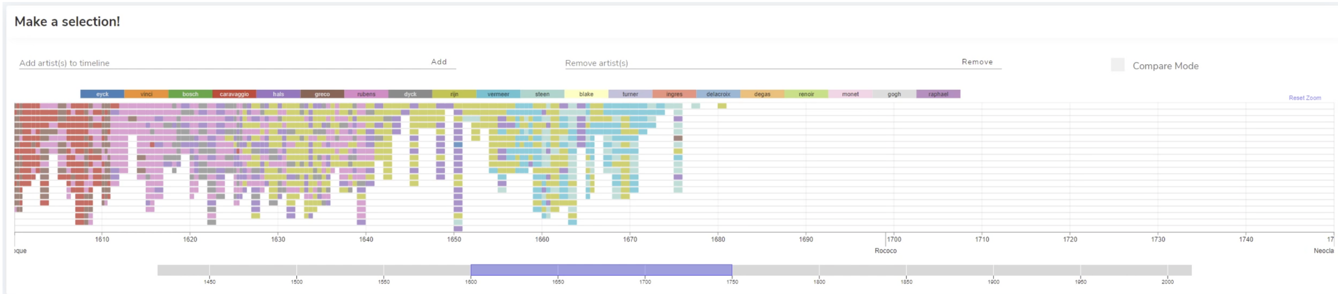

Figure 7: The interactive art timeline brushed to a specific time range as shown by the blue selection box at the bottom, before making a specific selection.

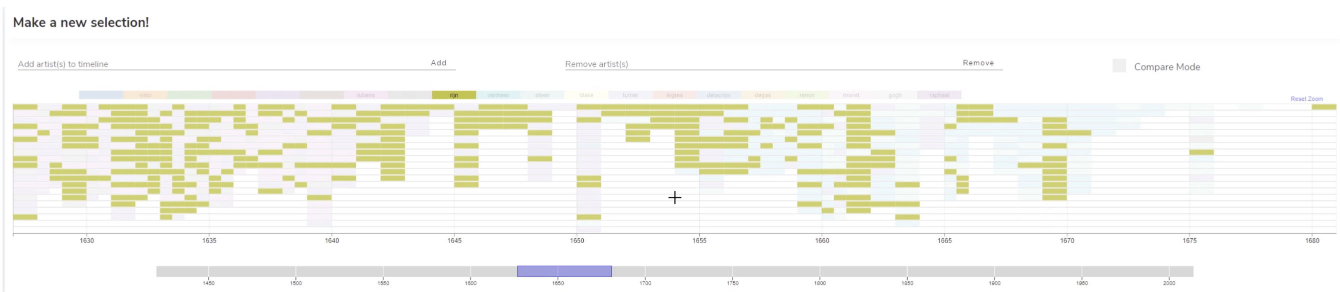

Figure 8: The interactive art timeline after making a selection for Rembrandt van Rijn.

maps, etc. The GAN learns to generate new paintings based on the whole variety of paintings. This can result in unrealistic images since these basically are a concoction of these different paintings. The dataset contains lots of maps, which causes the generator to almost only generate images of maps for multiple centuries. These factors show that a more careful selection of images will lead to a more meaningful solution compared to our current models.

7.2.2 Front-end

The front-end is assessed with the multiview visualisation rules.

7.2.2.1 Diversity This rule states that multiple views can be used when there is a diversity of attributes, models, and other information components. The front-end satisfies this rule since not only multiple charts are presented but also text components.

7.2.2.2 Complementarity This feature states that multiple views can be used when different views bring out correlations and/or disparities. This rule is not that evident in the application. The components are all about dominant colours and describe the art pieces that are presented. However, the link between these components could be made more evident.

7.2.2.3 Decomposition The visualisation satisfies this rule since the information is split into manageable chunks and provides insight into the interaction among different dimensions.

7.2.2.4 Parsimony The parsimony can be found in the interactive timeline. This is implemented in an interactive manner so that it scales according to the chosen options. Because it is desired to have an overview of all information components regarding the art pieces it is deliberately chosen to spread the information on the page to be able to grand this overview.

7.2.2.5 Space/time optimisation Interaction is costly and rendering can take seconds. As the user is able to make multiple paintings, artist or time period selections during a session, this is the most costly part of our visualisation. The interaction costs were lowered by applying as many actions automatically following an action from the user. The design choice is made to integrate socket.io events that return the data for individual components. This way the processes of the components are separate which makes it possible to visualise the components that are less computationally expensive sooner. This way the user can study this visualisation while waiting for the other components to render.

7.2.2.6 Self-evidence The rule of self evidence could be made more apparent by using identical colours in different graphs to highlight the correlation or similarity.

7.2.2.7 Consistency This rule states to make interfaces for multiple views consistent, and make the states of multiple views consistent. The multiview rule of consistency is applied by using uniform cards and headers. The application of this rule could be made better to correlate the colours among plots.

7.2.2.8 Attention Management To apply perceptual techniques to focus the user's attention on the right view at the right time it is implemented that the newly rendered components are placed before the already present ones. That is, the timeline is pushed to the bottom when the graphs appear. This enables the user to incline at analysing newly rendered components rather than the already present ones.

7.3 Further Studies

Some further studies to extend this project could be to create other visualisations which provide more insight in the dataset. For example, to provide the amount of art pieces in one class. This way the user has more insight on how many instances the generated image will be based on. In addition, a way to further evaluate the generated images, it would be interesting to construct an evaluation measure that measures the similarity in dominant colours from the existing images and the generated images. This way the evaluation can be quantified. Another very interesting feature would be to add the

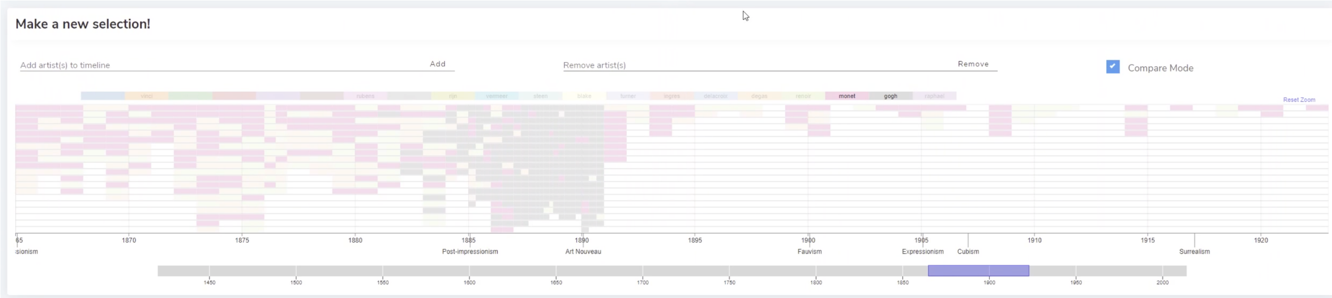

Figure 9: The interactive art timeline depicting the selection of two artists, Monet and Van Gogh, when in the compare mode.

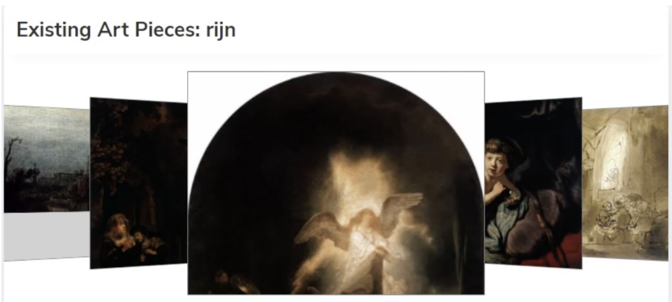

Figure 10: Image carousel depicting existing art pieces of Rembrandt van Rijn.

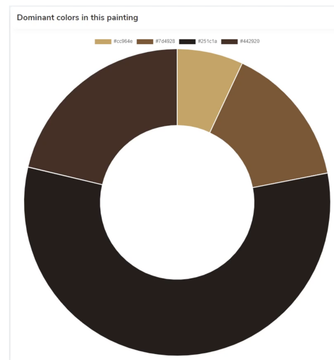

Figure 12: Dominant colour pie-chart corresponding to the generated images as shown in figure 11.

Figure 11: Generated art piece in the style of Rembrandt van Rijn.

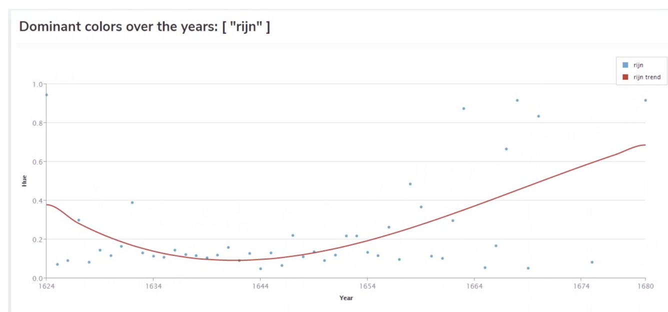

Figure 13: Scatter-plot depicting the dominant colour hue change over the years for Rembrandt van Rijn.

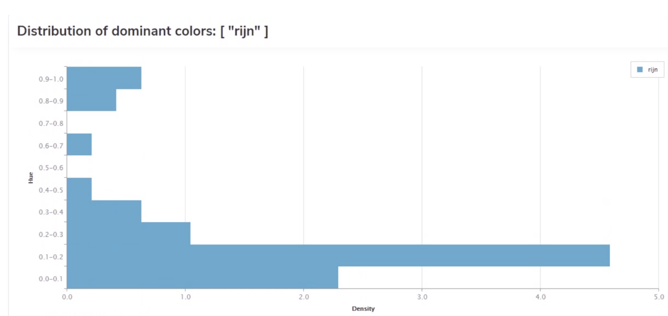

Figure 14: Histogram depicting the summary of use of dominant colour hues by Rembrandt van Rijn.

Figure 15: Extra information on the selection of Rembrandt van Rijn, taking from his Wikipedia page.

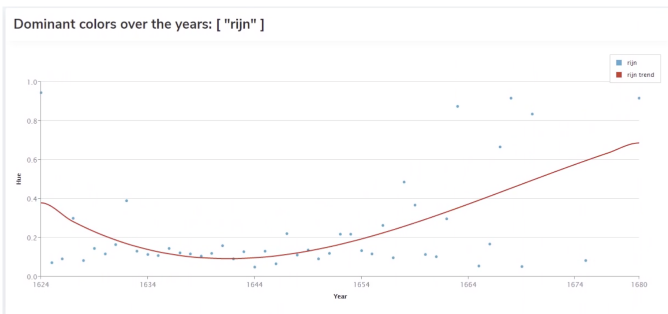

Figure 16: Scatter-plot depicting the dominant colour hue change over the years in compare mode for Monet and Van Gogh.

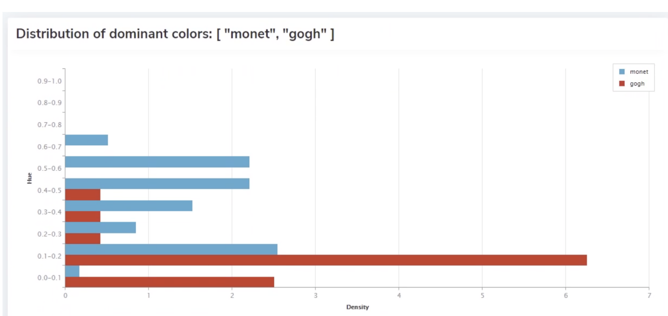

Figure 17: Histogram depicting the summary of use of dominant colour hues in compare mode for Monet and Van Gogh.

option for the user to generate images based on the dominant colour, next to artist and genre.

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APPENDIX A

Figure 18: Existing art pieces of the genre Baroque

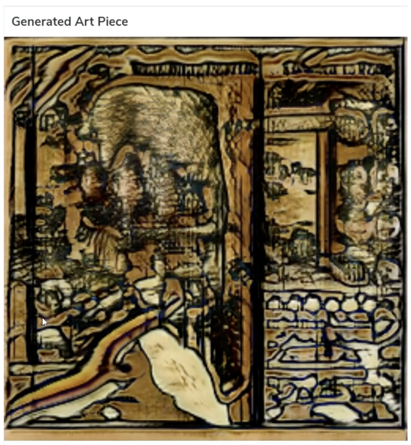

Figure 19: Generated art pieces of the genre Baroque

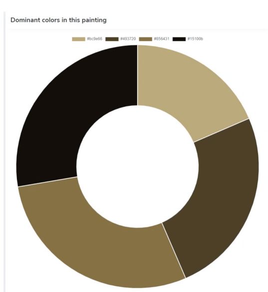

Figure 20: Dominant colours of the generated art piece of the genre Baroque

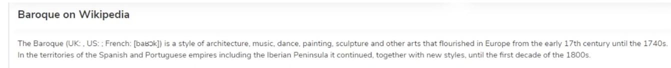

Figure 21: General information of the genre Baroque

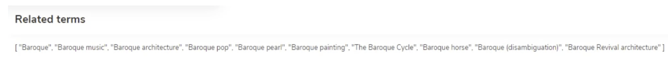

Figure 22: Related terms to the genre Baroque

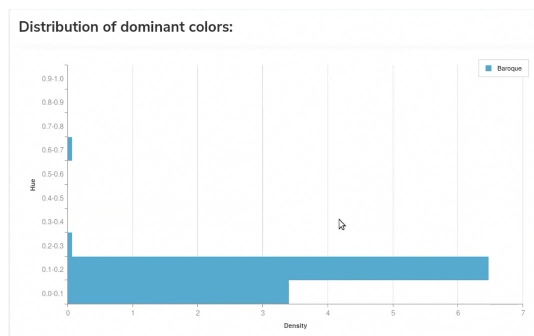

Figure 23: Distribution of dominant colours of the genre Baroque

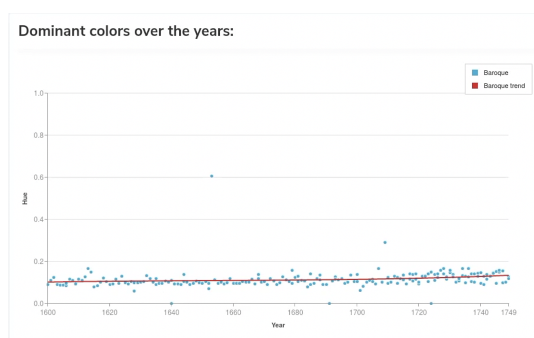

Figure 24: Dominant colours over the years of the genre Baroque

APPENDIX B

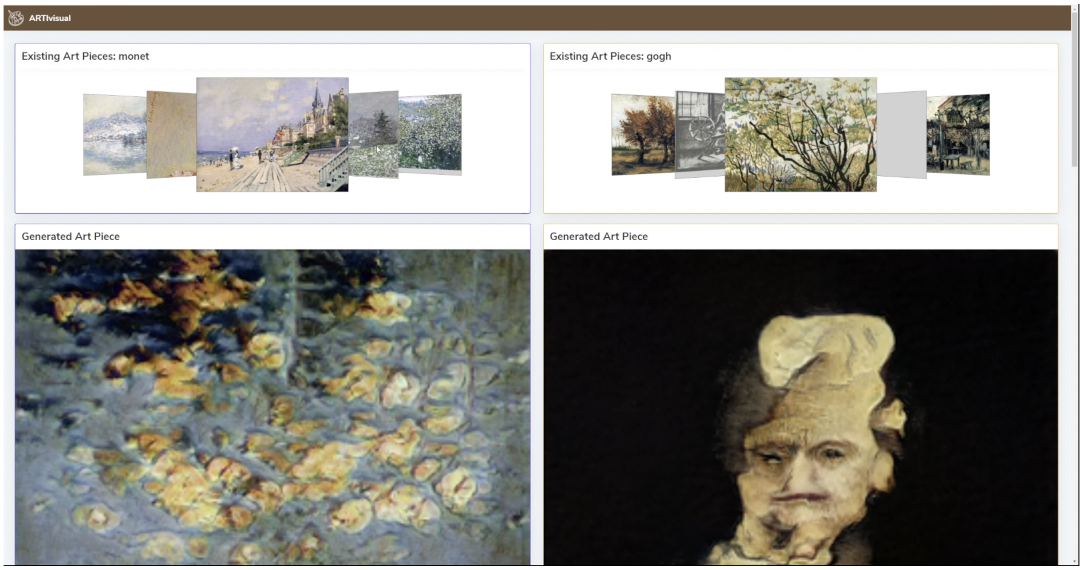

Figure 25: Compare page of Monet and Van Gogh

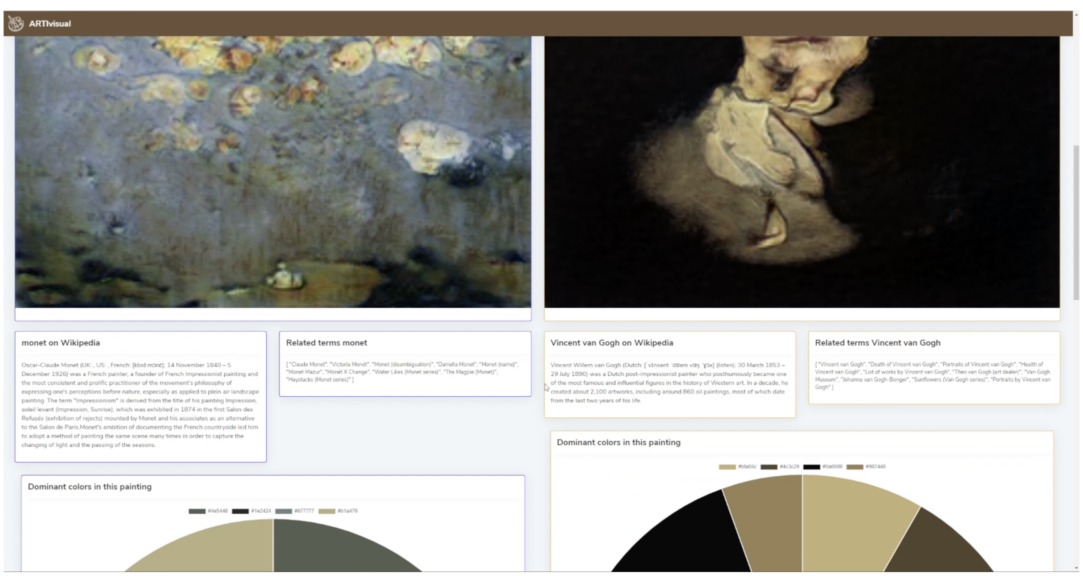

Figure 26: General information about Monet and Van Gogh

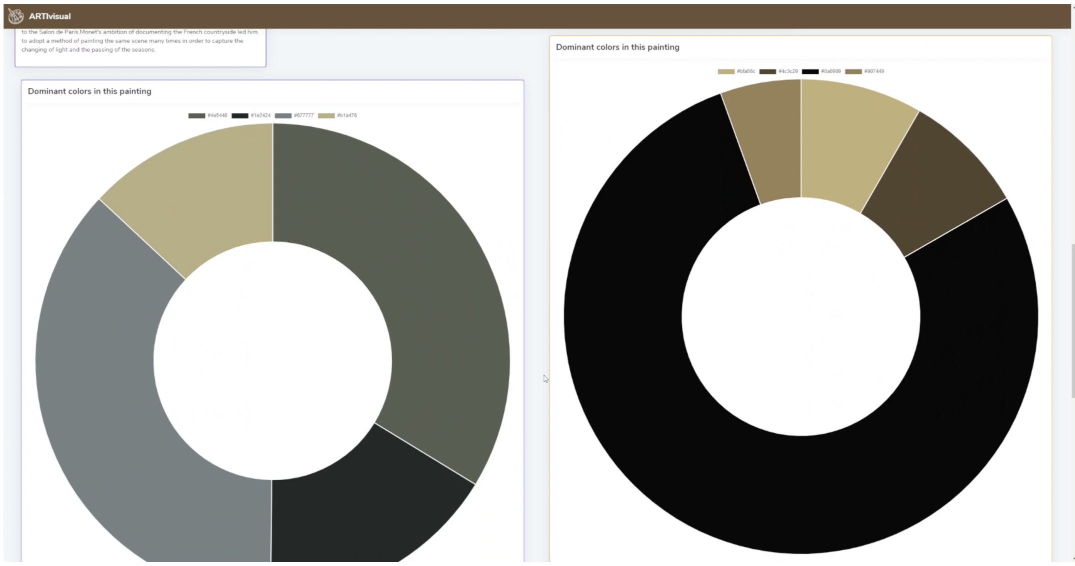

Figure 27: Comparison of dominant colours in generated art piece of Monet and Van Gogh

Figure 28: Comparison of distribution of dominant colours of Monet and Van Gogh