

# The zombification of Art History: How AI resurrects dead masters, and perpetuates historical biases

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## ABSTRACT

In the past few years deep-learning Artificial Intelligence (AI) neural networks have achieved major milestones in artistic image analysis and generation, producing what some refer to as art. We reflect critically on some of the artistic shortcomings of a few projects that occupied the spotlight in recent years. We introduce the term *Zombie Art* to describe the generation of new images of dead masters, as well as *The AI Reproducibility Test*. We designate the problems inherent in AI and in its application to art history and suggest further art-related implementations for these new tools.

## KEYWORDS

Artificial Intelligence; Art; Deep Learning Neural Networks; Generative Art; Deep Art; Rembrandt.

## 1 | INTRODUCTION

Artificial Intelligence (AI) has been in the public eye and imagination for many years already, with endless scenarios describing the disappearance of different jobs and human skills, which would be overtaken by intelligent machines. Artistic creation is no exception, as the question of mechanized artistic creation has been tantalizing human imagination since the emergence of the modern computer [1] for some decades. Recent breakthroughs in machine learning—celebrated in mass media (Mirani, 2014; Rayner, 2016; Graham, 2018)—herald the achievement of this goal. While we applaud the progress in machine learning, neural nets, image recognition and manipulation, we question whether they constitute a major artistic breakthrough, at least in their current form. We point out the major problems that afflict this use of AI technology in an art historical context, rife with culturally biased interpretations. We suggest that by

rethinking their conceptual goals and uses, more interesting AI-generated art may be created. We further foresee a new frontier of AI-based art history.

For the purpose of our discussion we rely on three AI art projects that have attracted a substantial amount of media attention recently: The Dutch *Next Rembrandt* project, created by a multidisciplinary group of researchers, analyzed the style and content of a large number of Rembrandt's paintings with custom-created AI, then used the data to produce a "new Rembrandt portrait" (ING et al., 2016); The *DEEPART* project, created by a German group of computer scientists, provides proof of concept that AI can successfully separate the content of an image from its style, to combine the style of one image with the content of another. Their well-known example is an image that reproduces a picture of the contemporary city of Tübingen in the style of Van Gogh's *Starry Night*. The same software also generated images in the style of other artists based on that same Tübingen photograph (Gatys, Ecker and Bethge, 2016a, 2016b) [2]. A slightly different project was created by the Parisian collective, Obvious Art. The collective generated painterly portraiture images based on a large dataset of 14th to 20th century portraits analyzed by a deep learning neural net. It received a lot of publicity when one of its generated images, *Edmond de Belamy, from La Famille de Belamy* was auctioned by Christie's in 2018 for USD 432,500 (Obvious Art, 2018; Caselles-Dupré, 2018; Schneider and Rea, 2018; add the reference to the christies item) [3].

Our approach to the art world is as a complex whole, which in itself is part of a larger, more complex whole: culture. As Clifford Geertz writes:

art in any society is never wholly intra-aesthetic, ... The chief problem presented by [art] is how to place it within the other modes of social activity, how to incorporate it into the texture of a particular pattern of life. (Geertz, 1976, p.1475).

Indeed, the “cultural significance” of art varies between cultures and periods. Though, we consider the three projects introduced above with interest and attentive criticism, the broader and more significant questions are those that involve the effects of current AI art on the art world as a whole. Namely, AI-generated art has a potential to change the environment of the art world, or in Bourdieu’s terms, the potential to affect and change the art world’s “habitus” (Bourdieu, 1990) [4]. Such a perspective, when applied to AI-generated art, can be innovative and significant. An example of such a perspective is the manner that the new technology of photography, appearing in the mid-19th century, influenced modernist movements in painting, and was influenced by modernist painting in return (Trachtenberg, 1980). Additionally, we present aesthetic evaluations of the three above-mentioned projects. Yet, because these works were generated by the novel technology of AI deep learning nets, the criteria for artistic evaluation of such works has not yet adequately emerged. Hence, the terms used here for our evaluation are tempered and limited in number on purpose. We delineate a bare minimum of connected traits that can stand as a correlate of artistic interest, significance, and value in the context of contemporary culture. These include creativity, innovation and a sense of surprise.

## 2 | THE SPECTRE OF ZOMBIES IS HAUNTING AI ART

### 2.1 AI AS FORGERY?

As much as the advances in AI and Neural Networks should be applauded, one might consider projects such as *Next Rembrandt*, *DEEPART*, and *Edmond de Belamy, from La Famille de Belamy* be generating “Zombie Art.” “Zombie” because these machine algorithms generate paintings that attempt to simulate the style and content of masters that have been dead for centuries: a new painting in the generic style and content of Rembrandt, images in the unmistakable style of van Gogh, or any given image in the style of Munch’s *Scream*. The possibilities are literally endless. Such images are technical assemblages existing in the space between the past and the present, life and death. These images are like the living dead or specters: they are zombie images, at once

“dead” and “alive.” While it may certainly be considered an achievement to create a new artistic category such as AI-generated Zombie Art, we question its actual artistic significance and interest. Are not these images “deepfakes”? (Knight, 2019) [5] Or simply put: are they not just machine-made forgeries?

Zombie Art is not limited to machines. Human artistic forgeries of dead masters, such as the case of van Meegeren’s fake Vermeers from the 1930s can also be considered Zombie Art. The only difference is that the human forger injects at least a modicum of creativity to the forgery (though the goal of creating a passable fake will tend to limit such creativity). In van Meegeren’s case, human forgery still relied on the artistic prowess and creativity of the forger, making the forgery unique. Therefore, human generated “Zombie Art” might be more accurately, and less provocatively, termed simply as “forgeries.”

The creators of the Dutch *Next Rembrandt* in their video themselves describe their project along the lines of creating a forgery:

because a significant percentage of Rembrandt’s paintings were portraits, we analyzed the morphology of the faces in these paintings, looking at factors such as gender, age and face direction. The data led us to the conclusion that the subject should be of a Caucasian male with facial hair, between 30-40 years old, in dark clothing with a collar wearing a hat, and facing to the right. (ING et al., 2016, 1:33-1:55)

Such a description of Rembrandt’s (or any other artist’s) characteristic subject-matter, which neatly corresponds to popular perceptions about him, constitutes the *sine qua non* of forgery; the real challenge, of course, is to fool the experts.

### 2.2 AVERAGING THE GRAND MASTERS

The main criticism of these projects is that their forgery-like mimetic aim constitutes precisely the reason why they are artistically underwhelming. We realize, though, that the emergence of such AI-generated works already questions the current meaning of artistic value. As interesting as these projects may be from a technical perspective, reading into the algorithmic process itself, we realize that this process actually undermines the value of the original artworks themselves, before they were transformed into datasets.

The generation of "new" Rembrandt paintings based on the datafication of his original oeuvres emphasizes the repetitive dimensions of his creativity, in a way that has so far eluded the human viewer of his work, thus diminishing the singular interest and value of Rembrandt's actual paintings.

However, all three projects share a deeper problem. Because the aim of these projects is to emulate the style and/or content of a specific artist's oeuvre, the generating process of such images will inexorably zero in only on the most clear-cut characteristic and recognizable perimeters of the artist's style and/or content. By definition, this leads such projects to focus on the artist's most obvious and redundant subjects and/or style traits, in order to generate his or her signature style and/or content. Examining the *Next Rembrandt* project illuminates this inescapable drift towards the artist's most distinctive and well-known traits, that are, unfortunately also the tritest characteristics of his oeuvre.

Yet Rembrandt did not acquire his reputation through a mere repetition of subject and style. As art Historian Christopher Wright writes in his book on 17th century Dutch painting: "one of the secrets of Rembrandt's subsequent reputation is [the] variety" of his oeuvre (1978, 172). Such variety is often divided into: history paintings of Biblical and classical subjects; landscapes; animals; self-portraits; portraits of family members; genre scenes of Dutch life; and portraits (Rembrandt Painting Net, 2019). Against this rich variety, *Next Rembrandt's* highly circumscribed focus on portraits of a Caucasian male in dark clothing etc., appears limited. Moreover, as the *Next Rembrandt* project video explains, once it was decided that the "new" Rembrandt would be a portrait, they used various algorithms to extract average shapes of facial features such as eyes, noses, and mouths and facial proportions from Rembrandts' portraits.

The project's drastic limitation of the image content together with the idealized averaging of facial features as input data are the major reasons why its "new" Rembrandt portrait is underwhelming. While the "new" portrait achieves a high level of painterly technique, this attainment is undermined by the very statistic averageness of its subject and style. Due to this averageness, for us, *Next Rembrandt's* "new" generated portrait is ultimately dull since it does not contain any artistic surprises or novelty.

Similar dynamics are operating in the image generation of both the *DEEPART* and Obvious groups, although their algorithmic method is

different. *DEEPART* attempts a balancing or averaging between content and style, in order to generate "visually . . . appealing images" (Gatys, Ecker and Bethge, 2016a, 6). Yet, creating pretty images by balancing the content/style parameters does not necessarily make for significant artistic images. In fact, many of the images created during the process, displaying unbalanced weightings of the content/style parameters are of greater artistic interest than the featured balanced ones, since they contain more surprises than the end result (Gatys, Ecker and Bethge, 2016a, 7, Fig. 3).

In Obvious's project, the dynamic of averaging or limitation is operational in a different manner. Obvious's generation of portraits was achieved by inputting its deep learning neural net with "training data set of more than 15,000 portraits" (Schneider and Rea, 2018). However, the input data is not as varied as presumed, for two reasons. The first is artistic: historically, the genre of portraiture is the most durable and least changing genre in art history, due to its highly circumscribed conventions [7]. The second is methodological and has to do with the selection process of input images; On their website, the Obvious collective explain: "[w]e carefully select a large number of input images with common visual features. The goal is to create a new sample that shares these features." Together these two factors emphasize the commonality, rather than the variety of the input images.

Hence, all three projects are conceptually and operationally confined in a variety of ways, including limited inputs, the search for common features, averageness or an emphasis on an artist's most redundant traits. All these conspire to limit and restrain artistic creativity, novelty and surprise. However, there is an even deeper challenge, one that is *innate* to AI deep learning algorithms: the manner in which a data set is utilized to train deep learning algorithms requires a critical consideration. The *Next Rembrandt* project provides an example of this predicament in a revealing way.

### 3 | WHEN AI PERPETUATES THE BIASES OF ART HISTORY

When training a deep-learning neural network on a given dataset, the choices and uses of datasets can perpetuate already existing biases, as well as introduce new ones. Such issues have become prominent with AI applications in recent years.

One such bias, which appears to be present in two out of the three projects discussed here, is the absence of female artists and female

representations. Feminist theorists of art history and the art world, such as the pioneering Linda Nochlin, have long argued that an entrenched sexism towards women is prevalent in art; from the treatment of women artists to the use of women—especially, but far from exclusively in the context of nudes—as objects of representation (Nochlin, [1971] 1988). Examining the three projects, the most glaring sexist bias is displayed by *Next Rembrandt*. The project's official video opens with brief images of two portraits, the first of a male subject, the second of a female subject (0:00-0:05). After a few talking heads introduce the project, the title “Step 1, Gathering the Data” appears over a mosaic of eighteen Rembrandt paintings (1:18-1:20). The majority of the paintings are portraits of single men or groups of men, but they also include two portraits of women and three group paintings in which a woman or women are present. Then the voiceover explains: “The first step was to study the works of Rembrandt in order to create an extensive database.” Then the title “Step Two, Determining the Subject” appears superimposed on a split screen featuring two other Rembrandt portraits, one of a male subject, the other of a female subject (1:32-1:36). The voiceover then explains:

“Because a significant percentage of Rembrandt's painting were portraits, we analyzed the morphology of the faces in these paintings, looking at factors such as *gender*, age and head direction. The data led us to the conclusions that the subject should be a portrait of a Caucasian male . . .” (ING et al, 2016, 1:33-1:48, emphasis ours).

Statistically speaking, their conclusion is correct. It should be noted, however, that from Rembrandt's existent oeuvre of just over 300 paintings, includes around 100 portraits (self-portraits excluded) of which 39 are of single women, along with three double husband-and-wife portraits. In other words, well over a third of Rembrandt's portraits are of women subjects. Furthermore, women appear in 38 of his 108 historical paintings; as well as in four paintings from his eight landscapes and six allegory paintings (Category: Female, 2019; Rembrandt Painting Net, 2019).

Even more significant is feminist art critique's widespread interest in Rembrandt, championing his representation of women in his portraits and historical paintings. Hammer-Tugendhat writes:

Rembrandt's portrayals of women have become some of the most famous images in the history of Western Art, promoting emotive reactions among his strongest critics and enthusiastic admirers alike.

This is the first sentence in the catalogue of the exhibition Rembrandt's Women held in London in 2001. Rembrandt's portrayals of women... have garnered hefty amounts of criticism since the 17<sup>th</sup> century. At the same time, his representations of femininity have also been received quite positively by [contemporary] gender-critical scholars... (Hammer Tugendhat, 2015, p.15).

Like other scholars, Hammer-Tugendhat emphasizes how exceptional Rembrandt portrayal of women is in relation to his contemporaries. Though, as a person of his time and culture, Rembrandt's paintings generally conform to the gender-norms of the period: “within the frame of what was historically possible, Rembrandt indeed created an alternative image of femininity” she writes, explaining that: “Women are granted subjectivity” and “are even allowed an active gaze... [as well as] thoughts and doubts [in his portraits]. Rembrandt presents his women [including nudes] with empathy.” (Hammer Tugendhat, 2015, p. 158)

Yet, all this highly significant information is casually omitted from the *Next Rembrandt* official video by simply invoking the “all powerful” data set: “The data led us to the conclusions that the subject should be a portrait of a Caucasian *male*” (ING et al, 2016, emphasis ours). The very decision to create a portrait of a male subject, unquestioningly recapitulates the gender biases of traditional art history. Simultaneously, it flattens and diminishes the complexity of Rembrandt's oeuvre. Indeed, this decision, based on the most basic kind of “head-counting” appears to undermine the more complex possibilities that AI-generated art has opened up. It does not pay tribute to the depth of Rembrandt's oeuvre, nor does it pay tribute to his progressive representation of women within the limits of that period. Rather, the choice made by the creators of the Rembrandt project reflects a most traditional reading of art history.

Such is not the case for the *DEEPART* project. Although in the two papers published by the *DEEPART* group, only paintings by famous male painters are presented as visual examples of their ability to abstract the style or content from an image, yet this is not an inherent bias of the

algorithm itself (Gatys, Ecker and Bethge, 2016a, 2016b). Since the *DEEPART* algorithm can combine the style of any image with the content of any other image, there is no algorithmic foreclosure against a specific gender of the kind found in the single image generated by the *Next Rembrandt* project. As for *Obvious*, the group sampled a large dataset of portraits, that we surmise included females as their subjects—although it's unclear whether any women artists were among the painters—due to the fact that they generated and exhibited a number of female portraits as part of their fictional “Belami family” (Caselles-Dupré, 2018).

#### 4. | OPEN-ENDED EXPERIMENTATION VERSUS PRESPECIFIED GOALS

The projects discussed here can be seen as an evolution of computer-based generative art, which started with the early computer age. The early artistic experiments with computers and current AI art share many common features: the creation of the algorithms or neural nets; tweaking them; selecting the best images from a large output of generated images. Therefore, it is instructive to place AI art works in the genealogy of generative art. However, there is a significant difference between these two approaches to using the computer creatively, and it boils down to using deep learning networks rather than non-learning algorithms. In other words, since earlier generative art did not set forth to reproduce old masters, it did not have to “learn” anything.

The objective to reproduce old masters highlights another significant difference between early 60s-70s computer-generated art, and current generative art. Early computer art was undertaken in the spirit of open-ended experimentation, with no specific goal in mind. As Max Bense and Reinhard Döhl proclaimed, “The artist today realizes accomplishments on the basis of conscious theory and deliberate experiment” (1964, 9; See also Nake, 2005, 60, 93; Nake, 2012, 77). In contrast, *Next Rembrandt*, *DEEPART* and *Obvious* are all directed towards their predetermined and specific objectives, thus determining the modus operandi of these projects. Of course, these projects included substantial experimentation, yet this type of experimentation was most likely motivated by engineering rather than artistic purposes. Experimentation was not open-ended, but was rather of an instrumental kind, attempting to arrive at their predetermined goals of imitative forgery-like artistic representations. Indeed, these projects’ well-defined teleology constitutes one overarching reason why their results have only limited artistic value.

#### 5 | ART IN THE TIME OF AI: SUGGESTIONS FOR ALTERNATIVE USES OF DEEP LEARNING AI ART NETS

Since art and artistic value are cultural and historical phenomena, the emergence of powerful new AI image analysis and generation technologies affect the current artistic ecosystem. Indeed, throughout history technology has always influenced and impacted art, like in the case of the ancient production of pigments, the invention of oil-based colors or the invention of photography, to give a few examples.

The appearance of these new artistic AI based tools, calls for new modes of artistic creation, and artistic analysis. To illustrate this point, let us take Marcel Duchamp, for example, and ask what if his entire oeuvre—with all its different styles, mediums and genres—was inputted into a deep learning neural network that has been trained to extract or distill a single artist’s style, content or both. What are the chances that such an AI neural network might succeed in this task and reproduce a new, yet recognizable Duchamp? It would probably not be able to do so successfully. While most artists have a single “mature style”, there are artists that among their prominent signature is their simultaneous (or rapidly changing) creations in many artistic styles, genres and mediums. The names of Francis Picabia, David Smithson, Gerhard Richter and Sigmar Polke, among others, come to mind [7]. Inputting the entire oeuvres of such multitudinous artists into the hypothetical deep neural network described above, might not yield impressive mimetic results. This principle could act as an “AI Reproducibility Test.” This test would consist of checking whether a deep learning AI net, inputted with the entire oeuvre of a single artist, would be able to generate novel images commensurate with that artist’s oeuvre, or not. Perhaps it is possible for such a hypothetical test to yield a clear demarcation between artists whose oeuvre allows for such generation of images, and those whose oeuvre does not. But, more realistically speaking, the outcome of such a test would be a spectrum of results, ranging from high ratings for artists whose oeuvre easily abets the generation of new images in their signature style and/or content, to low ratings for those artists with which the neural networks will only achieve limited or unsatisfactory results. This might well lead to interesting new insights regarding artistic practices. It is possible that in the future the relative ranking of contemporary, working artists in the AI Reproducibility Test would become significant; thereby, influencing artists to attempt at creating oeuvres that would

produce lower Reproducibility Test ratings, in order to perpetuate the “aura” of [human] artistic creativity.

Keeping in mind the AI-generated art projects discussed here, it would seem that interesting results could come from artists whose Reproducibility Test ratings are at the lowest part of the spectrum; i.e., cases where neural nets would not be able to satisfactorily distill their style and/or content. Such supposed “failures” would serve as a kind of constraint on the neural net’s tendency to focus on the most reoccurring features of an artist’s work. Thus, generating novel images based on hard to reproduce artists will generate “off-kilter” images and this would likely generate more surprising, unexpected, and potentially more creative images.

To conclude, the strength and significance of AI based projects, such as the ones reviewed here, is not in producing new, out of context paintings by dead masters, but rather in the creation of a new approach to art history in the context of 21st century. If our machines can now paint a “new Rembrandt”, and separate between style and content, can we use them to learn new things about the processes, significance, and meanings of contemporary art?

## ENDNOTES

[1] The idea of art created by computers already appears in Alan M. Turing’s seminal paper “Computing Machinery and Intelligence,” (1950) which introduces what is now known as the Turing Test. The first question the interrogator asks the computer and human in the Turing Test is: “Q: Please write me a sonnet on the subject of the Forth Bridge” (434). However, computer generated art really took off during the 1960s, due to better and more powerful computers and output devices. One of the inaugural major exhibitions of computer-generated art was “Cybernetic Serendipity” (1969) at the Institute of Contemporary Arts in London, curated by Jasia Reichardt. In the introduction to an issue of “Studio International” devoted to the exhibition, Reichardt writes:

[With the advent of computers,] The engineers for whom the graphic plotter driven by a computer represented nothing more than a means of solving certain problems visually, have occasionally become so interested in the possibilities of this visual output, that they have started to make drawings which bear no practical application, and for which the only real motives are the desire to explore, and the sheer pleasure of

seeing a drawing materialize. These people ... have started making images, both still and animated, which approximate and often look identical to what we call ‘art’ and put in public galleries. (Reichardt, 1969, p.5)

[2] Currently, the *DEEPART* group has opened a website, where people can select and send two images, one for content and the other for style, and the software generates a third image which is the amalgamation of the two images (DeepArt.io, 2019).

[3] There has been controversy around Obvious’s use of its GAN algorithm, since it is virtually a copy of an algorithm created by Robbie Barrat and uploaded by him to GitHub. (Flynn, 2018).

[4] Bourdieu defines “habitus”: “as systems of durable, transposable dispositions, structured structures predisposed to function as structuring structures, that is, as principles which generate and organize practices and representations that can be objectively adapted to their outcomes without presupposing a conscious aiming at ends or an express mastery of the operations necessary in order to attain them” (Bourdieu, 1992, 53).

[5] The term “deepfakes” is currently a catch-all term for forgeries of images, videos, audio, etc., that are exceedingly difficult to detect due to their high quality achieved by advanced AI deep learning neural networks to generate or manipulate them.

[6] In portraiture painting, by definition, the focal point is always the face of the person; the face almost always looks at viewer or is slightly turned; there are only three central formats: full figure, “half-shot” (only the head and torso are pictured), or head-shot (showing only the face and shoulders); the figure is nearly always either standing or sitting, generally in an interior. It is exactly this strict convention that made the collective focus on portraits, as Caselles-Dupré, of the Obvious collective admits: “We did some work with nudes and landscapes, and we also tried feeding the algorithm sets of works by famous painters. But we found that portraits provided the best way to illustrate our point, which is that algorithms are able to emulate creativity” (Caselles-Dupré, 2018).

[7] Other contemporary multitudinous artists include for example: Bruce Nauman, Albert Oehlen and Martin Kippenberger.

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