# Machine Learning and Notions of the Image

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## Abstract (EN)

This thesis addresses how current notions of image production remain tied to historical ideas which often prove inadequate for the description of visual artefacts of machine learning (ML). ML refers to the notion of simulating the process of information acquisition computationally, and when applied to the generation of images, it enables visual content to be influenced based on the statistical analysis of data. The increasing use of ML in image production highlights several aspects which have been present in older forms of media, but which now take on new forms and relevance, especially within artistic contexts. This research seeks to clarify the mediating role played by visual technologies and to demonstrate how images produced using ML offer new ways of approaching theories of the image.

Images exist at the interstices between human perceptual experience and its technological mediation, which is especially relevant as the development and implementation of technologies offers new possibilities to produce visualisations from data. In so doing, technological mediation tangibly augments relationships between how images are produced, experienced and interpreted. The present incorporation of ML into various forms of visual media offers insight into this issue by enabling images to be produced as the result of the statistical analysis of datasets. Computational relations which are extracted and inferred between features within images help to construct learned representations which are in turn used to generate new images. This results in a form of computationally-determined representation which is informed by the interpretive processes performed by machines.

Artists have taken great interest in the potential of ML, in an aesthetic, but also a processual capacity, often considering its relation to human vision. Their productions offer insight into novel aspects of ML in the creation of images through experimental practice which is informed by theory and by art history. Using and reflecting on ML, often in novel or reactionary ways, artistic and humanistic perspectives provide vital counter-narratives to those of computer science (CS), and which facilitate cross-disciplinary understanding.

In spite of the hype which surrounds it currently, ML does not present an entirely novel approach to image production and rather builds upon existing modalities and narratives surrounding the technical production of images. Notions of technically produced images often lean heavily on historical narratives regarding the technical production of images, even perpetuat-

ing inaccuracies from them. These tend to misconstrue images either as inherently accurate reflections of reality or as the product of artificial perception and genius, by virtue of their engagement with technological processes. This research therefore adopts a media archaeological approach, in order to understand how processes that have been present in visual media much longer than the use of ML continue to colour discourse.

## Abstract (DK)

Denne afhandling ser på, hvordan aktuelle opfattelser af billedproduktion stadig er forankret i historiske idéer, der ofte viser sig utilstrækkelige, når man skal beskrive visuelle artefakter inden for maskinlæring (ML). Med ML forstår man det at simulere informationstilegnelsesprocessen ved hjælp af computerberegninger, og når ML anvendes til generering af billeder, bliver det muligt at lade statistisk dataanalyse påvirke billedindholdet. Den stadig hyppigere brug af ML i billedproduktion sætter fokus på en række aspekter, der allerede var en del af ældre medieformer, men som nu antager nye former og relevans særligt i kunstneriske sammenhænge. Den her præsenterede forskning søger at klarlægge den formidlende rolle, som visuelle teknologier spiller, og at vise, hvordan billeder, der produceres ved hjælp af ML, åbner for nye måder at tilgå billedteorier på.

Billeder eksisterer i feltet mellem den menneskelige perceptuelle erfaring og dens teknologiske formidling, hvilket er særligt relevant, da udvikling og implementering af nye teknologier giver nye muligheder for at frembringe visualiseringer ud fra data. Teknologisk formidling udvider dermed helt konkret de indbyrdes relationer, mellem hvordan billeder bliver produceret, oplevet og fortolket. Den måde, hvorpå ML i dag inkorporeres i forskellige former for billedmedier, giver et indblik i dette ved at gøre det muligt at producere billeder, der er et resultat af statistisk datasætanalyse. Computerberegnede relationer, som udledes og antages at forbinde givne træk i billeder, er med til at fremstille afledte repræsentationer, som derefter selv bruges til at generere nye billeder. Det resulterer i en form for computerbestemt repræsentation, som er baseret på fortolkningsprocesser udført af maskiner.

Kunstnere har vist stor interesse for potentialet i ML, som en æstetisk, men også en processuel dimension, idet de ofte betragter ML stillet over for menneskets synsevne. Deres værker giver en indsigt i nye aspekter ved ML i frembringelsen af billeder gennem en eksperimentel praksis, der er baseret på teori og kunsthistorie. Ved at bruge og reflektere over ML, ofte på nye eller reagerende måder, skaber kunstneriske og humanistiske perspektiver vigtige mod-narrativer til dem, vi finder inden for computervidenskab, og bidrager dermed til en tværfaglig forståelse.

På trods af den hype, der i dag omgiver ML, så repræsentere ML ikke en fuldstændig ny tilgang til billedproduktion, men bygger snarere oven på eksisterende modaliteter og narrativer omkring den tekniske billedproduktion. Idéer om teknologisk fremstillede billeder lægger sig ofte op ad

historiske narrativer om teknisk billedproduktion og viderefører endog nogle af deres fejlagtige antagelser, hvor billeder ofte misfortolkes som enten naturgivne præcise gengivelser af virkeligheden eller som et produkt af kunstig oplevelsesevne og genialitet i kraft af deres forbindelse til teknologiske processer. Den her præsenterede forskning anvender derfor en mediearkæologisk tilgang for at forstå, hvordan processer, der har eksisteret i de visuelle medier meget længere end anvendelsen af ML, forsat præger diskursen.

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I believe that nothing in this world — not even the invention of media and computer art — can alter the task of art, which is to reveal the eternal in the finite. (Kittler 2007)

## Introduction

In recent years, machine learning (ML) has received a great deal of attention from artists, as well as theorists, considering what implications it holds for visual culture. Artistic practice incorporating ML provides novel examples and perspectives regarding the interplay between the visual and non-visual aspects of images, and the interpretive processes performed by humans and machines. Current technical possibilities have lent new modes of production, aesthetics and modalities to images, yet are often theorised in ways that connect to, elaborate upon or reiterate existing notions of what images are, how they behave, and what significance they hold. This has contributed to a lack of consensus concerning what may be considered the defining attributes of images. The present research addresses this lack of clarity by examining how recent applications of ML in visual art contexts expand upon existing notions of the image.

ML is a subfield of artificial intelligence[1] (AI) "in which machines 'learn' from data or their own 'experiences.'" (Mitchell 2019, 8). When applied to the generation of images, ML enables images to be informed by the process of learning. This may affect how the resulting images appear, how they behave and how they are understood. Producing images as the result of algorithmic procedures emphasises the processual and non-visual aspects of images, as well as provoking speculation about the potential autonomy of highly automated image production from human vision and agency. The use of ML to produce images thereby also presents several theoretical issues concerning how such artefacts are to be interpreted.

Artists' explorations often put forward unorthodox perspectives as to how ML may be used, misused or seen in new ways. Their investigations have also had a great deal of crossover and collaboration with theory, either through artists' writings or through interdisciplinary cooperations. The work of Harun Farocki, Trevor Paglen and Hito Steyerl is especially notable for its *transversal* (Gansing 2013) nature, cutting across disciplinary lines, but these are just a few names among many who have made significant contributions in this respect. Combining practical and theoretical enquiry has offered vital insights into the implications of ML for visual media, which

1: AI itself is rather complex to define, but the Stanford's 100 year report on artificial intelligence offers the following "operational definition" of AI: "a branch of computer science that studies the properties of intelligence by synthesizing intelligence." (Stanford University 2016, 13) This working definition is attributed to Herbert A. Simon. Further discussion of the connection between ML and AI at large can be found in Chapter 1 (p. 30).

reciprocally inform one another. For instance, artists experiment with theories in a practical capacity, from which new knowledge may be drawn.

## Background

Algorithmic tendencies were already present in visual media before the current hype around ML and AI, but they are gaining significance as the use of ML becomes more widespread. The capacity for images to be formalised algorithmically enables them to be executed according to specific constraints and procedures, which also affords them aspects of mutability, to be articulated in variable formats. This grants images greater potential for images to be stored, printed, duplicated or electronically transmitted, often resulting in an equivocation between image, data and text. Such attributes fit with the principles of new media, as described by Lev Manovich (2001, 27–61), but may also be traced back to much earlier precursors involving the implementation rigorous constraints and instructions in the production of images, whether analogue or digital.

Formalising images in terms of algorithmic processes also enables the production of images to be performed in a highly automated fashion. The participation of machines in image-making has long been a contentious issue in art history. The tendency to overstate the autonomy of machines has fueled discrepancies regarding the authorship, as well as the truth value, of images. Photography, for its part, has been the subject of heated debate concerning the role played by the camera in the photographic process, often minimising the role played by the photographer. As a result of this logic, technically produced images have historically been framed as expressions of the capacities of the machine — separate from its creator — which is uncritically believed to result in higher levels of objectivity in technically produced images.

The photographic aesthetic, which emphasises verisimilitude between representation and referent, has been the dominant visual paradigm of the past century and continues to be important within digital media. This is in spite of the fact that a significant divide may exist between the aesthetic qualities of an image and the processes involved in its production. While this has been present in older forms of visual media, including painting, drawing or photography, the generation of images based on learned patterns in datasets disrupts the apparent direct visual referential connection between image and the world that is found in other forms of image-making. The levels of interpretation which occur between the visible surface of an image and the processes behind it render such referentiality unreliable. Frieder Nake

(2008) explains this in terms of interfacing between the (visible) surface of an image and the (processual) *subface* behind it, in which visual media is understood as exceeding the visual, but not reducible to process alone. Following the perspective of postphenomenology (Ihde 1993), visual technologies not only modulate perceptual experience through their aesthetic qualities but also play an interpretive role therein.

The capacity of visual technologies to mediate or to act as analogues for biological vision recalls cybernetic perspectives on perception, which draw comparisons between various kinds of visual systems and processes, whether biological, mechanical or computational. Notions of nonhuman vision performed by machines have been explored by artists, as well as theorists, who have sought to visualise, to problematise or to re-envision the way that machines process visual information. Among them, Harun Farocki's (2004) concept of *operative images*[2] (17) – or operational images – has been especially significant. The influence of Farocki's ongoing artistic and theoretical work examining the interpretive role played by machines can be seen, for example, in Ingrid Hoelzl and Rémi Marie's (2015) *softimage* and Paglen's (2014) *invisible images*.

The complexity of relations between human vision and images is a central feature of visual technologies. It demonstrates how closely attuned visual media are to the human subject, as well as how delicate visual mediation is as a result. The overlap between the simulating capacity of images and the parameters of human vision is fundamental to the mediation performed by images, but it also forms the basis of dissimulation. Technoscientific approaches to visual media have provided new ways of visualising data, but have also proven their capacity for error and manipulation. This is especially noticeable in adversarial approaches, in which the visual properties of an image may operate on a different plane than the way the same image is analysed by a machine. For this reason, adversarial approaches have been used by numerous artists in efforts to hinder, to demonstrate or to interact with aspects of machine vision[3] (MV) and computer vision (CV).

Highly automated processes of image production not only make the differences between the processing of visual information by humans and machines starkly apparent but also reveal the error in considering automated forms of image production as autonomous from human influence. The incorporation of ML into the production of images thereby adds to an al-

2: Farocki has used several variations of this term, but for clarity, "operative image" is used in the continuation of this thesis.
3: MV is differentiated from CV as being connected with robotics, concerned with spatial tasks in addition to the computational tasks performed by CV.

ready complex area of discourse surrounding the technologically mediated nature of image-making. Though attempts have been made to distinguish current from traditional forms of visual media – and their related theories – these are compounded together with the wealth of discourse which already exists on the topic of the image.

The deceptively simple question, “What is an image?” (Mitchell 1986), demonstrates that while pointing to an example of an image may be a simple task, defining what constitutes an image is fairly difficult. As a result of the diversity of technical processes that may be employed in the production, dissemination and performance of images, a wide variety of even conflicting attributes may now be ascribed to images. This makes it effectively impossible to define the image through a single set of criteria, leading to what has been referred to as the “crisis of the image” (Belting and Jephcott 1994). An abundance of terms have arisen in response to this problem, each of which addresses various facets of images, yet no master theory proves suitable to grasp the image in its entirety. Instead of cover-all theory defining what an image is, there is a multitude of different — often competing — theories to describe certain of its many potential attributes. Rather than being reinvented through a succession of technological paradigms, as is suggested by the continual attempts by theorists to rebrand the image, visual media contain echoes of the numerous technologies — and theories — which have been compounded, one upon another, before arriving at the current state-of-the-art.

ML-produced images draw attention to the importance of process in tandem with aesthetics. In older forms of visual media which have entailed highly complex processes of mediation through the execution of algorithmic procedures, the process of production certainly played an important role in how images thus produced were received. Yet the relative obscurity of ML processes, which are often not readily apparent in the resulting images, necessitates higher degrees of knowledge and interpretation on behalf of viewers, to understand them. Such a discrepancy makes the products of ML image production artefacts of many levels of interpretation and of mediation, which often engage in abstraction as a heuristic device for grappling with the complex processes involved.

In addition to altering how images appear and how they behave, algorithmic processes also influence images in terms of how the role of those processes is understood. While ML gives over the orchestration of image production processes in large part to be determined by computational processes performed by digital computers, what is more significant is how these processes are defined concerning data and its interpretation. In this sense, the visual content of images comes to be equally as important as how it is mediated. This includes the methodological approach as well as the level of the interface through which it is encountered. This interfacing quality of images makes them intermediaries between the human perceptual system and the world via technological, biological and conceptual apparatus. Images thereby influence not only visual experience but also how that experience is interpreted.

As technological developments augment the possibilities of image production, they also reshape cultural expectations and understandings of how images behave, their value and their meaning. For example, growing knowledge as to ML's simulating capacities and potential for error acts as a counterweight to the extremes of techno-optimism and techno-pessimism which have often accompanied it and other visual technologies in the past. In such a way, image-making technologies play a vital role in interpreting the world around us, in addition to being subject to interpretive processes in their reading.

## Research Question

This research seeks to develop an understanding of how the use of ML — especially in artistic contexts — contributes to re-evaluations of the image. It therefore responds to W. J. T. Mitchell's (1986) question, "What is an Image?" not by answering it, but by asking:

*How does machine learning expand understandings of images?*

Current methods of image production, such as those employing ML, build and expand upon notions, methods and techniques which have existed for much longer. This means that not only can attributes and modalities of newer media be found in older and often distantly related media artefacts and processes, but also that they continue to be framed in terms of theories concerning older modes of image-making.

The increasing importance of algorithmic processes in image production reveals discrepancies between various understandings of images. This includes divulging changes in how images have been theorised over time concerning new visual technologies. There is a need for clarification of existing thought regarding the growing importance of ML in visual media. Rather than seeking to define — or to redefine — the image, this research aims to contextualise current practical examples in relation to theory.

As a paradigm in image-making, ML departs from the norms of other visual technologies, such as photography, by enabling the creation of images based on learned patterns in data, rather than capturing visual likenesses of real-world objects in a direct sense. The production of images is subject to the interpretive processes exerted on therein, both in terms of human perception and subjectivity, as well as those imposed by the technological conditions of that production.

Visual media are tied to the parameters of the human perceptual framework in the sense that they are reflective of how and what we see, as well as how we interpret it. This means that visual technologies augment what is perceived, as well as altering how it is interpreted. The use of ML in image-making thereby intervenes not only in the technological mediation of perception but also plays an interpretive role which mediates between the performance of visual tasks by machines and the intentionality and perceptual experience of humans. This renders common dichotomies between visual and non-visual, human and machine insufficient for understanding the complexity of image production processes.

Drawing connections to older — even analogue — techniques and devices, this research considers how historical examples have contributed to the current production of images using ML. A contextual understanding of how image production is influenced by ML is established by identifying and differentiating novel attributes from existing tendencies. Considering image-making processes in terms of their role as mediators of human perception — rather than either entirely focused upon or divorced from it — enables a departure from already well-trod approaches to the image.

Theorising the image as either a materially static, primarily visual object and the product of human creativity, or as an invisible, ephemeral process that is only accessible to machines, fails to adequately address the levels of nuance that occur in images. Instead of attempting to debunk these ideas, this research seeks to meet them together by establishing common ground between them. Cultivating similarities between seemingly disparate forms of visual media and ideas regarding the evaluation of images, this research develops a perspective on images that is focused primarily on their role as mediators of perceptual experience.

To develop a thorough account of how theories of the image are impacted by the intervention of ML in image production, current methods of image-making are examined in relation to historical tendencies in the use of technology in visual media. We therefore examine how longstanding cultural narratives around the production of images have shaped current understandings of image-making technology. This involves performing an analysis on representative examples from contemporary art and art history, as well as drawing insights from technical experimentation. Instead of treating ML approaches to visual media as isolated from past forms of image-production, employing an approach to this topic informed by media archaeology enables us to see how current theories of the image act as a continuation of — not a distinct break from — existing notions of the image.

## Methodology

The nature of this research topic crosses the boundaries of several fields of research, which necessitates an interdisciplinary approach. Artistic practices involving ML in image-making bring together knowledge — and often practitioners — from a range of disciplines including art, the humanities and computer science (CS). The visual productions they create may have relevance within these fields of research but are also of wider significance as visual culture becomes subject to mediation involving ML on an increasing basis. The holistic approach of this research aims to develop a more nuanced view of the topic than existing discipline-specific views have up to this point been able to provide.

It also seeks to bridge disciplinary divides by establishing common language and knowledge across several areas of research. While each of the areas touched upon by this research contributes aspects of competency to this study, they each bring with them their own assumptions, conventions and languages, which may hinder understanding across disciplines. There are notable differences between the ways that artists and researchers in the humanities or in CS speak about the same topics. Not only do they approach them from different angles, but they also have different traditions and terminology for describing the research that they do.

There is a lack of unifying discourse and synthesised understanding between — and even within — fields, which this thesis seeks to address. While the exploration of ML within art and the humanities has led to fresh approaches and articulate criticism, it has also at times proven uninformed, even clichéd. Appropriation and examination of ML by non-experts acts at times as a reckoning with, and at others, as a re-articulation of, the entrenched mythology that surrounds AI. In discussions on the topic of ML in humanities and art contexts, for example, I have found there is a tendency toward abstraction, approximation and recourse to metaphor. While these may be helpful for a number of reasons, including developing ways of understanding and communicating complex processes, it often lends itself to imprecision, misunderstandings and inaccuracy. On the other hand, while CS excels in technical terms, it often lacks the criticality provided by more humanistic perspectives.

Developing a contextually based account of this topic that is relevant to interdisciplinary contexts compiles knowledge from several fields to develop a technically descriptive, yet theoretically-grounded approach. This enables important technical aspects to be described in such a way as to enrich a humanistic view of this subject matter. It also discusses technical processes and theoretical concepts in such a way that they are understandable to those who are not specialised in those respective topics.

Therefore, an effort is made here to limit the use of unnecessary jargon, which has the potential to be more vague than clarifying — even alienating — for readers. I have therefore adjusted my writing style in order to better communicate with audiences across the several disciplines involved in this research. A hybrid perspective is therefore not only vital to the extraction and synthesis of existing ideas, but it also helps to prevent the potential propagation of misinformation.

Artistic practice contributes to this research by offering an understanding of the processes and methods involved in ML by engaging with them directly. As an artist, my interest in this research topic is not limited to curiosity about its conceptual dimensions but is also directed at how it plays out culturally. By adopting a hands-on approach within this research, I also challenge myself to understand its inner workings in new ways, outside the lens of art and theory.

During the course of this PhD project, I conducted a series of experiments seeking to better understand the modalities involved in the use of ML to produce images. Admittedly, the practical side of this project led to the humbling experience of struggling with ML on a technical level, which brings its own insights to the project. I now understand from experience that some aspects of this material may be grasped in different ways by those who are approaching it initially than by those who are more familiar with the technical processes involved.

That said, approaching this topic by way of a background in art and media studies brings with it the benefit of seeing certain aspects from a different perspective than that of experts in ML. For example, the fact that modalities of generative ML processes are in certain ways reminiscent of much older image-making processes is understandably not a central issue for CS researchers. But within the present research, it is important to understand how today's visual technologies have been influenced by those of the past, as well as their related discourses.

Discussion of my own artistic works related to the research topic allows me to pinpoint and discuss particular modalities that are significant to this research. This includes the projects *Identifying Abstract Art* (Lee 2018) (p. 92), *Artbreeder Experiment* (Lee 2019a) (p. 44), *Deconstructing Representation* (Lee 2019b) (p. 113), *image machine / machine image* (Lee 2019c) (p. 60) and *the image is a machine* (Lee 2019d) (p. 26). Being a practitioner has also facilitated close contact with the community of other artists and researchers in the area of research, which has been a vital resource in terms of knowledge exchange throughout the development of this project.

One of the central contributions of this research is a historically-grounded survey of ML's application in the production of images, which enables current forms of visual media to be contextualised in relation to those that have preceded present image-making technologies. It also contributes to ongoing discourses regarding the technical nature of the image, as well as the influence of ML on art, by seeking to make internal discrepancies that have persisted in theories about the image more apparent.

*Media archaeology* (Huhtamo and Parikka 2011), which seeks to build connections to technologies from the distant past, is a significant influence on the approach of this research. The drawing of comparisons between examples that may appear disparate, but that demonstrate critical tendencies and relations, is used as a method to enrich the understanding of the present context. This demands that we think in more nuanced terms about visual technologies' relation to their precursors.

Examining a particular media artefact relative to its historical precursors allows, for example, digital screens to be seen in light of examples from cinema and pre-cinema (Mannoni 2000), such as the magic lantern. Performing such a "screenology" (Huhtamo 2012) facilitates a deeper understanding of technologies of the screen than examining contemporary media alone may afford. According to Huhtamo, this enables media constructs like the screen to be made visible, as attention is usually fixated on the content mediated, as opposed to on the medium itself.

Here, the image is examined as a construct, enabling us to compare its various ways of being, as opposed to merely approaching the image by in terms of its appearance. Just as the screen may become invisible, so, too, do the edges of the image. Considering what and how images may be now, in comparison to examples from history, allows us to see how certain aspects and ideas have remained the same while others have been altered by changing technological conditions and cultural contexts.

The focus of this research is on the artistic use of ML which highlights the process involved, the aesthetic qualities of the resulting images and their combined significance. Images produced by *generative adversarial networks* (GANs) (Goodfellow et al. 2014) (p. 39), for instance, have proven especially popular among artists due to both the degree of pictorial realism they provide and their engagement with generative and interpretive processes. Because of the importance of not only the visual but also the processual nature of algorithmic media, such explorations provide especially insightful perspectives on this topic. GANs, which are among the most popular ML architectures currently used by artists are therefore a central focus.

The adoption of ML in artistic practices often goes beyond visual experimentation with the aesthetic and technical capacities of the technology. Instead, numerous artists and theorists have engaged with the processes, power structures, history and ideas behind ML and AI. The practices which form the central part of this investigation strike a contrast with the more technically focused explorations heralding from CS research. Often the latter are more technically than conceptually driven, in which case ML is applied for the purpose of creating visual effects as opposed to engaging to a greater extent with their conceptual significance. In contrast, artistic applications of ML which consider the meaning, context and nuances of the technology lend greater insight into this subject, offering critical reflections on the mediating role of technology therein.

The review of literature and technical and artistic projects conducted in the early stages of this research led to the discovery that there was some work concerning the algorithmic behaviour at work in images, but that it did not substantially address the relation between the technical and theoretical dimensions of this issue. Discussion with others within my field of research helped form a consensus that there is a lack of work in this specific area. Identifying this problem helped in clarifying my research question and establishing a framework for the continuation of the research.

Close readings are performed on a representative selection of artistic, theoretical and technical projects that have had a defining impact on the field. These are contextualised within a historical framework and in connection to central themes in current theoretical discourse. Documentation of my own artistic explorations of this topic is used to complement these central figures in the field, with the intention of building theory from artistic practice.

Through close examination of the modalities of exemplary artistic works employing ML, we consider how this reflects new and longer-term tendencies in image-making technology. The examples covered are compiled with the intention of creating a representative selection of projects that demonstrate the state of the art in the use of ML in contemporary visual art during the three-year study period of this research (01/10/2017–30/09/2020). This includes the work of artists who are highly regarded as well as those who are less established but push forward discourse in this area. These are contextualised in relation to examples from art history and from CS research that develop a clearer picture of how to understand these practices.

Analysing the artefacts covered in this thesis is a complex, qualitative task because it is so multifaceted and spans centuries of technological development of image-making processes. Many of the examples covered touch upon several issues at once or could be used to make a variety of different points. The delineations used in this thesis are by no means the only reasonable way of dividing the material but they can be seen as thematic sections that allow it to be approached in a focused manner. This enables often overlooked or otherwise inconspicuous commonalities between diverse examples to be made apparent.

This research considers the use of ML in visual art as a way of developing a deeper understanding of its relation to existing theoretical stances on image production. To achieve this aim, a mix of methods is employed, combining theoretical analysis with practical experimentation. The foundation of the thesis consists of an interdisciplinary review of literature and of projects, examining theoretical, technical and artistic landmarks in the history of image production. From analysis of notable artistic and technical works in relation to existing theories around the image, a new understanding is developed of how the images created using ML meaningfully depart from earlier notions regarding what an image is and how it may behave.

The methodology employed in this research addresses the particularities of the research topic by looking closely at concrete examples in connection to theory. The main axis of this approach is the comparison of theories and technologies of image production over time. Considering how visual artefacts of ML fit into a larger history of technological development as well as surrounding discourses on the image makes it possible to identify and to understand aspects of novelty in comparison to older forms of media. Using this knowledge to identify historical tendencies also allows critical misconceptions about the technological mediation of perception and agency that is present in the production of images to be addressed. Together, these primary threads of this research facilitate an intensive examination of theories on the image and how they are altered by the use of ML.

Several aspects are excluded from the scope of this research in order to highlight certain features and to avoid areas that do not contribute significantly to the aims of this research.

The selection of examples that are discussed in this thesis has ultimately been based on qualitative judgements about which are most reflective of the relevant issues within the field. These assessments are constrained by subjective interpretation, personal taste and situated knowledge, which are specific to Western perspectives on art. In acknowledgement of this, the present thesis hopes to underscore that there is a multitude of different perspectives on this topic. Non-Western artefacts of algorithmic media have been examined to a limited degree in the early stages of this research, but are not discussed here as they fall outside the scope of this PhD thesis.

Computational creativity and generative art are other issues that are not considered to any great degree in this research. The main reason for this is that creativity is not a significant topic within discourse on art, because it is taken as a precondition for art, rather than a novelty. Therefore, instead of examining computational creativity itself, this research approaches how ML functions as a complement to creative practice. For related reasons, generation as a tendency in image-making is prioritised over the specific examination of generative art. This is due to the fact that generative art tends to focus heavily on the implementation of generative processes without engaging critically with the technical processes involved or with the historical narratives that surround them.

Beyond its direct use for image generation, algorithmic processes also inform design processes and aesthetics. This can be seen in applications such as parametric — or algorithmic — design (Parisi 2013), in which algorithmic processes structure a great variety of media outputs. As Manovich (2018) demonstrates, ML and AI may also play an analytical role in the interpretation of cultural data, including images. As significant work has already been done concerning the systematic implementation of ML in the design, organisation, visualisation and interpretation of vast amounts of data, this research does not go into great depth in addressing these issues.

Although ML raises many questions around privacy, bias, fairness, truthfulness and manipulation in visual media, this research does not focus on ethical issues, except when directly relevant within the scope of the research. The ethical dimensions of ML and AI are too broad to thoroughly investigate here and would require limiting the scope of research to that subject alone. Superficial investigations into the ethics of ML and AI have also become something of a cliché within theory and in art, which tend to reiterate the same findings without progressing further. Therefore, this research specifically focuses on how various ideas which surround the use of algorithmic media in turn shape visual culture.

### Thesis Overview

In order to give readers a solid foundation to build upon, Chapter 1 (p. 28) gives an overview of the relevant concepts, methods and historical context necessary to the progression of the research. It is intended as a guide to ML, specific to its use in the generation of images, in response to the issue that while many artists, designers and theorists are interested in ML, they may or may not be well-versed in its technical processes, concepts and terminology. Such an approach is critical due to a lack of related material explaining central aspects of ML relevant to visual media in a coherent yet understandable way for non-experts. It also focuses on particular methods and examples that give depth to current artistic practice involving ML. This includes looking at artificial neural networks, from the neuron upwards, to more complex neural networks and deep neural networks. It also gives a basic introduction to the ideas behind AI and its historical connection to cybernetics, which are often touched upon by artists and theorists.

Each chapter in the body of the thesis offers a different angle in the examination of how current artistic practices involving the use of ML relate to earlier precursors and their surrounding discourses. The major themes that are thereby addressed are: the impact of algorithmic processes on defining aspects of the image (Ch. 2, p. 48); the interplay between human and machine agency in the production of images (Ch. 3, p. 74); the mediating role played by technical methods and apparatus (Ch. 4, p. 96); and the impact these changes have on regimes of representation (Ch. 5, p. 113). This seeks to demonstrate significant changes or continuities that have occurred in discourses surrounding image technologies over time, as well as to familiarise readers with central ideas on the technical production of images. A number of transversal (Gansing 2013) narratives cut across these three chapters, which highlight similar modalities in and ideas connected to often disparate forms of media.

The integration of algorithmic processes into the production of images has had a resounding impact on the diverse range of qualities the resulting images may take on. Drawing connections between current forms of algorithmic media, such as those employed in the use of ML to generate images, Chapter 2 (p. 48) looks at much older — and simpler — instances in which algorithmic processes have shaped the qualities of images. This includes considering how methods for the production of images according to systematic, data-based procedures have enabled images to be transcribed in the form of code — to be executed by humans or machines. It also covers how geometry, optics and mechanical processes have become integrated into image production over time.

Analogue algorithmic processes and procedural practices enabled images to be executed according to rigorous sets of instructions and constraints. Geometrical systems of proportion shaped the structure of visual compositions. With the integration of optical principles, image-making techniques began to consider the position of the image as a mediator between visual perception and the world. Images thereby took on greater degrees of compliance with the parameters of human vision, as opposed to the ideological and symbolic dimensions of visual media. Mechanised production processes, such as the printing press and the camera, allowed the automation of aspects of image production. This facilitated the production of multiples, leading to theoretical difficulties around how such images should be evaluated.

Chapter 3 (p. 74) digs deeper into the connotations automation may hold for notions concerning the image. Comparisons between human and machine vision and agency are often brought up in regard to technologically mediated forms of image production but often suffer from oversimplification. Beginning with the way in which industrialised production processes caused a rift between evaluations of the products of human labour and those made by machines, we consider what implications this has held for the way in which automated image processes have been theorised.

As automation enabled machines to play a greater role in the production of images, they came to be seen as less directly subject to the intentions of humans. Machine-produced images came to be regarded as commonplace and less valuable than those produced by the human hand. The presumed autonomy of image-making machines also gave rise to was the myth of the machine as artist (Broeckmann 2019), diverting ideas about art as reflections of human genius into automated image production. Seen from a contemporary, posthumanist angle, this is suggestive of forms such as nonhuman photography (Zylinska 2017), in which highly-automated visual processing systems are considered to be estranged from the intentionality and vision of humans.

The differences between human and machine interpretation of images, which is especially visible in adversarial approaches to ML, offers unique insight into the interplay between these. While image production may be highly automated, there is a tendency to perpetuate mythology surrounding ML and AI, and the participation of machines in image-making, in which ML is often framed in terms of either cybernetic metaphor or as "black box". One consequence of this thinking has been the historical framing of machine-produced images as scientifically accurate, objective portrayals, despite the capacity they have demonstrated to manipulate appearances.

Chapter 4 (p. 96) problematises the polarities set out by existing theories of the image, which attempt to differentiate visual from non-visual aspects of images, and human from machine intentionality. Approaching this from the perspective of postphenomenology (Ihde 1993), we examine the mediating and hermeneutic role played by visual media. Not only do visual technologies act in a complementary fashion to the constraints of human vision, augmenting its capacities, but they also play an important role in how perceptual experience is interpreted.

Rather than theorising the participation of machines in image production as estranged from either human vision or intentionality, we examine the degrees of interaction and overlap that are found in highly automated forms of image production, such as those involving ML. The reformulation of the image in terms of processes performed by machines is especially well demonstrated in Farocki's (2004) work on the operative image. Examination of the concept of Umwelt (von Üexküll 1934), from sensory ecology, enables a deeper understanding of the perceptual mediation which occurs through visual technology.

Chapter 5 (p. 113) addresses the capacity to produce visual simulations from data. This considers the signifying role played by images in relation to the way in which images are produced and interpreted by machines. In contrast to earlier perspectives that have had a tendency to place blind faith in the products of technoscientific methods, we see that there is little certainty in the ability of visual media to provide reliable relations between images and the world. The visual outputs of ML can thereby be seen as representative of the statistical analysis of data, upsetting the expectation for images to act as representations of either human intellect and experience or empirical evidence of real-world phenomena.

The concluding chapter of this thesis (Ch. 6, p. 134) draws together and sums up the major arguments developed in this enquiry and the insights that have been gained as a result. This also includes projections for the continuation of the research.

The image is a machine. The image drives the machines that produce the image′.

The image may be more of a complex ecosystem, more like a pond than a mechanism. The image may be mechanical, electrical, chemical, biological.

The image may be automated or autopoietic. The image′ is latent in the instructions for its performance.

The image is not reducible to source code. The image has the potential for variability of expression.

The image′ need not be built. Non-expression is a potential expression.

The image is a database. It takes in information and spits out electromagnetic waves.

The image may or may not be visual. The image′ may be instantiated in other forms, such as sound. Sound-image′.

Too much concern is lavished on the image′, the face. Of greater consequence is the commodification of the image, human capital.

The image forgoes scarcity in favour of the fecund circulation of images′. The image may populate the world with innumerable images′.

The image′ has no inherent value. The image is a producer of value.

The image′ is derived from the distillation of societal value systems. The image is fat with the intellectual, creative and labour value it has consumed.

The image may or may not look back. The image may be used as a mode of interpretation of images′.

The image constrains what images′ may be produced from it. The design of images directly conditions the production of images′.

The image is concerned with method. The image is processual, procedural, a practice.

The image is a machine.

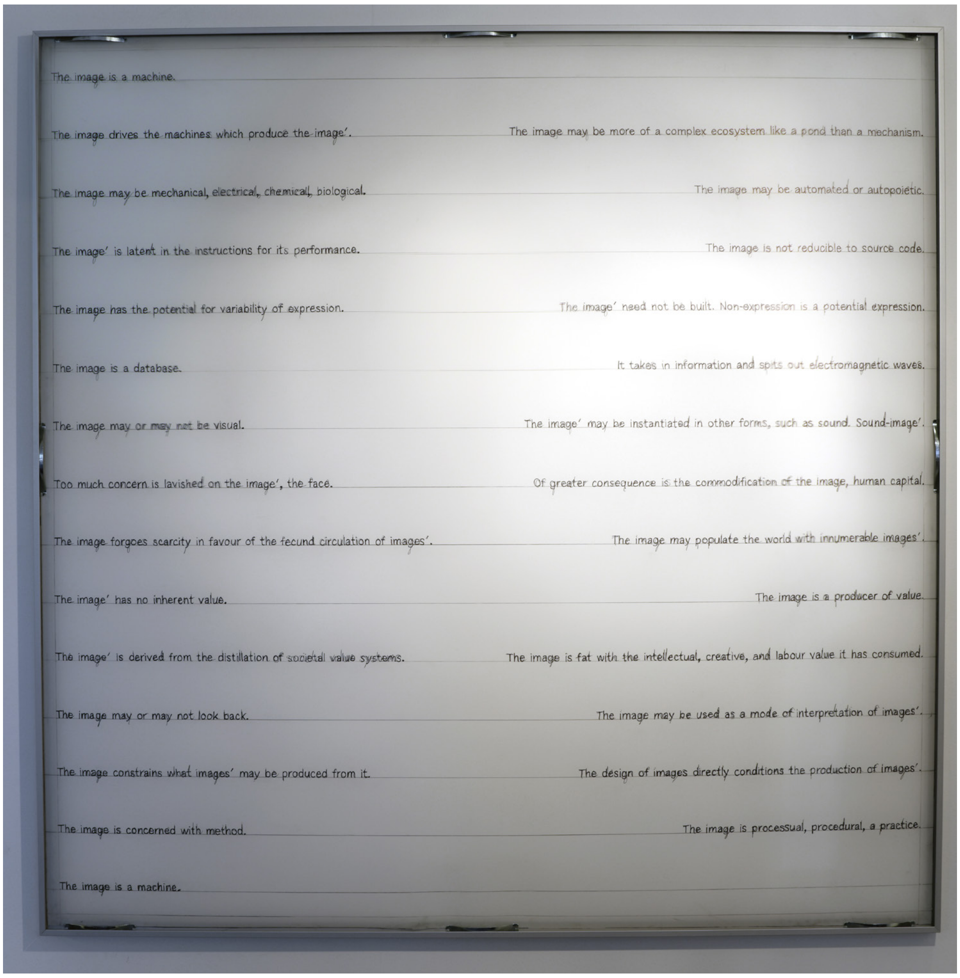



**Fig. 1:** *The image is a machine* (Lee 2019d).

To set the tone for this investigation, documentation of *The image is a machine* (Lee 2019d) gives an explorative overview of the major themes of this research. The work does not attempt to deliver a final word on defining the attributes of images. Instead, it seeks to grasp the significant characteristics of ML-generated images, poetically, allowing ambiguities in its distinctions. This text-based image is divided in pairs, which complement or correspond to one another. The prime symbol ( ′ ) is used to denote instantiations of algorithmically-informed images, in comparison with generalisations about images. Rather than being opposites, distinguishing between the image′ and the image explores how algorithmic qualities of current media may fit within or relate to existing notions of the image. Defining the image in this way helps us better understand certain aspects at work therein, but it also underscores the murkiness of this investigation. While it may elucidate some attributes, it also appears to obscure others in the process. This piece provides several different entryways from which to proceed onward in examining this topic.

# 1. Machine Learning in Image Production

## 1.1 Machine Learning

The approach of machine learning (ML) seeks to develop artificial intelligence (AI) systems with "ability to acquire their own knowledge, by extracting patterns from raw data." (Goodfellow, Bengio and Courville 2016, 2) AI, itself, is rather difficult to define, but is described well by Melanie Mitchell (2019) as " investigating the mechanisms of 'natural' (that is, biological) intelligence by trying to embed it in computers." (7) Learning, in this context, has to do with improving a *learning algorithm*'s development and adjustment of a *model* to better perform a task, given input data.[1] This is similar to the process of learning in animals, in which the accumulation of experience or information about the world, enables the improved performance of a given task. As such, learning in ML functions as a metaphor for the interplay between acquiring information, in the form of data, and implementing it, through the establishment of rules about how that information is to be interpreted.

In spite of the intentional distancing of AI from *cybernetics*, its influence is still noticeable in the tradition of drawing comparisons between diverse systems and processes, such as between the biological and the technical. These areas of research have diverged over time, yet draw from inter-related ideas, methods and often terminology. Words such as "intelligence", "thinking" and "cognition" are each packed with a number of meanings, describing a variety of different phenomena across different contexts (Mitchell 2019, 6). These descriptors help to illustrate some of the processes that are mimicked, for example in ML's progressive improvement of performance.

The overlap between other fields which have been influential to the prehistory of ML remains important to cultural understandings — and misunderstandings — of what is at stake therein. For example, familiar depictions from popular culture often treat ML, AI and *artificial general intelligence* (AGI) as interchangeable. HAL 9000 in *2001: A Space Odyssey* (Kubrick 1968), for instance, is an important point of reference within the cultural imagination as to what AI is or can be. HAL 9000 is more representative of AGI, which aims toward realising human-level intelligent behaviour using machines. than of ML or AI, but this kind of thinking is significant to our later

1: It is important to differentiate that it is the learning algorithm which is performed, and which remains constant over time, as opposed to the model, which is continually modified as a result of that process. This process is referred to as training.

discussion of how cultural mythology shapes theory and practice involving ML (p. 79).

ML also factors into cybernetic tendencies in thinking about visual technologies, and a general curiosity within the art world toward *posthumanism* (Wolfe 2009), which concerns the continuum of relations between the human and the nonhuman, and between the biological and the technical. These historical and theoretical ties are important as we consider notions of the autonomy of machines, both in the production of images and in automating their interpretation. This leads to two inter-related issues: the difficulty in understanding ML-produced images in comparison to human vision; and how ML exerts influence on the production of images. The disparity between how images appear to humans and the processes involved in their manifestation is especially important in situations in which there are noticeable differences in how these are either visualised or interpreted. This is a primary reason, for instance, that adversarial approaches have captivated the attention of artists (discussed in greater detail on p. 36 and p. 88).

Cybernetic ideas about relations between human and machine ability, intelligence and vision surface repeatedly within research on visual applications of ML and in many of the cases discussed in this thesis. This tendency is not exclusive to ML, and it draws on common ways of understanding older forms of visual media. In photography, for example, the camera may be seen as participating in the fusion of human and machine intentionality into a hybrid expression of agency (Verbeek 2008; Beloff and Jørgensen 2016). In this sense, the apparatus (Agamben 2006) acts as not only a physiological adaptation to better interact with the environment, but also as a modification of the sensory environment by providing new potentialities of perception (Beloff 2014). In such a *machinic assemblage* (Deleuze and Guattari 1980, 89), various components — including biological and inanimate elements — function symbiotically together. Tools can thereby be understood not solely as extensions of perception and ability, as described by Marshall McLuhan (1964), but also as interactants entangled within a complex perceptual system.

There are three main learning paradigms in ML: supervised learning; unsupervised learning; and reinforcement learning, which refer to the approach to data in how ML models are trained.

In *supervised learning*, a system is trained using labelled data from which it is able to make informed determinations or predictions when new data is encountered. For example, a model trained on images labelled with their respective image class (e.g. an image of a dog, cat, table, etc.) can be used to identify which class new example images fall into.

On the other end of the spectrum, *unsupervised learning* involves training a model using examples that are not assigned labels, meaning that the classification task is based on analysis of the properties of the input data alone. This kind of approach enables the structuring of unstructured data without explicit direction. An example of an unsupervised learning task is cluster analysis, which groups inputs together according to relative similarity.

*Semi-supervised learning* falls in a middle ground between supervised and unsupervised approaches, employing a combination of labelled and unlabelled data so that only a limited amount of labelled examples are necessary for training. In what is referred to as *self-supervised* learning, algorithms may even be evaluated by other algorithms, enabling a greater degree of automation.

*Reinforcement learning* differs from these approaches by requiring an autonomous agent to "learn to perform a task by trial and error, without any guidance from the human operator" (Goodfellow, Bengio and Courville 2016, 25). This is relevant to the use of ML to simulate the behaviour of artificial agents, common applications of which can be found in robotics or challenging AI to play games.

Visual applications of ML abound, such as the automated generation of images with particular visual attributes based on the analysis of a dataset. Our focus here is on the use of ML in processes of image production, but there is a great deal of interplay between *generative approaches*, which can be used to create images, and *discriminative approaches*, such as the classification of existing images. It is therefore also necessary to understand how discriminative processes contribute to the creation of images using ML. ML systems have proven highly successful at generating images of believable human faces (Wang 2019), applying the style of one image to another (Gatys, Ecker and Bethge 2015), or transforming users' doodles into cats (Hesse 2017). Discriminative applications of ML can be found in such situations as the use of facial recognition and image classification.

### 1.2 Neural Networks

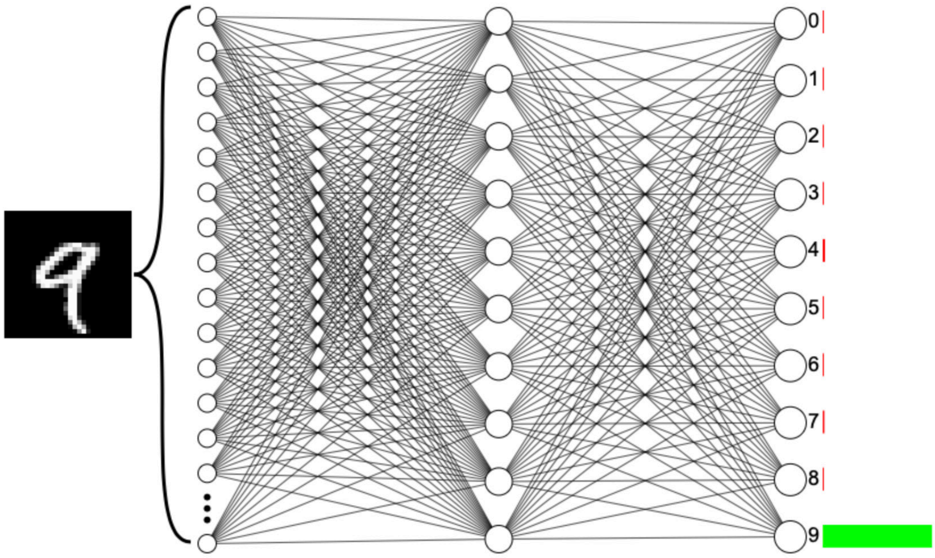



Fig. 2. Example of image classification showing weighted connections in a neural network (ml4a 2018).

*Artificial neural networks* (ANNs) (1943), or neural networks (NNs), are a highly influential and common kind of ML algorithm, which is inspired by the distribution of information processing performed by biological neurons. In the brain, information is processed through interconnected neurons, and the influence of individual neurons is adjusted in relation to others. Likewise, artificial "neurons", or nodes, in neural networks output values that are determined by weighted connections learned from data encountered during training. What this means is that each node governs the computational relationship between inputs and outputs in the system.

Given an input, an ML system may focus on different aspects, which together form representations of that data. A representation, in this case, is quite different than what the same word may mean in humanistic contexts. Here *representation* refers to a combination of learned attributes fitting a given class of image. To demonstrate, let's consider an ML system trained to categorise digital images of handwritten numerals. We input an image of the number "9", as in fig. 2. Each pixel value in the image is a *feature*, or a piece of information, about the image. In turn, the ML system may learn a representation, composed of several features, of the object or event being analysed (Goodfellow, Bengio and Courville 2016, 3). This could take the form, for example, of learning relationships between certain pixel values within the image, and the association of those pixel values with the label "9".

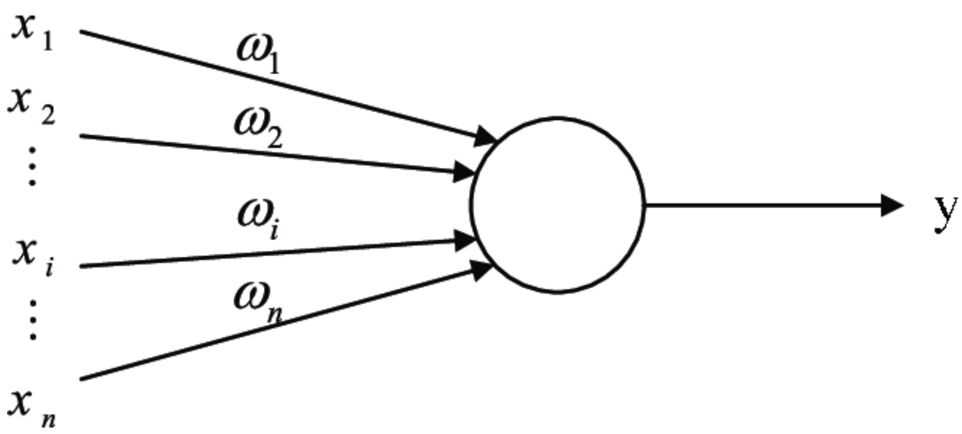



Fig. 3: *Schematic diagram of single-layer perceptron* (Shi 2019).

NNs have become more powerful and complex since the early stages of their development in the 1940s and 1950s, but they function on roughly the same principles. The historical experiment, the *perceptron* (Rosenblatt 1958), for example, could only differentiate between two categories of inputs, but the simplicity of the perceptron structure makes it helpful to demonstrate how NNs work. Fig. 3, above, offers a simple visualisation of a perceptron in order to illustrate the general concepts and processes entailed in a NN.

The input can be, for example, the brightness values of the pixels in an image. Each input value (x1, x2 … xn) is connected to the single neuron through weights (w). The neuron takes the sum (a) of the products of all the input values multiplied by the weights of the connections. Next, an activation function is applied, which is, basically, a linear classifier determining which class the input falls into. Depending on which side of the threshold the output (y) falls on, it is placed in one of two classes (0 or 1). The weights of the connections between nodes and inputs are adjusted based on the results of this process.

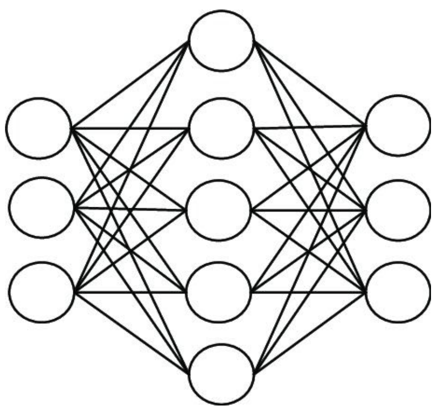


Fig. 4: *Schematic diagram of multilayer perceptron* (Shi 2019).

In recent years, *deep learning* and *deep neural networks* (DNNs) have become especially important terms within ML. DNNs expand upon the simple NNs previously discussed and are composed of several layers of neurons. The *multilayer perceptron* (MLP) in fig. 4, for example, builds upon the perceptron model with the inclusion of multiple layers. The "deep", in this case, refers to the feeding of data through sometimes many layers of neurons. Data may even be passed backwards through a NN in a process called backpropagation.[2]

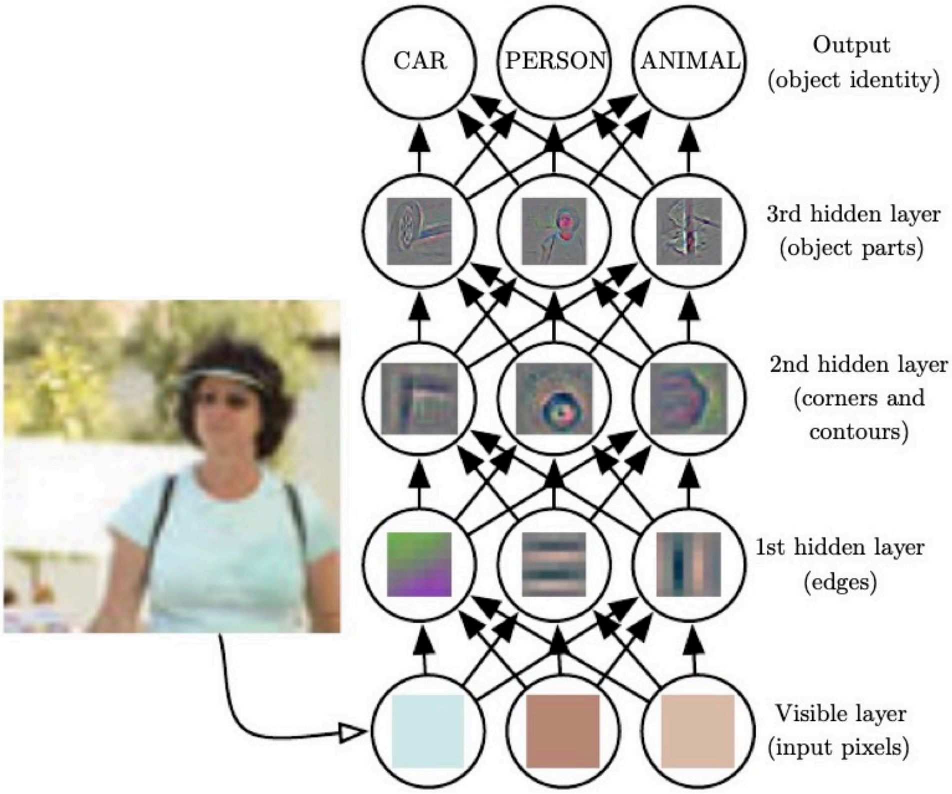



**Fig. 5:** *Illustration of a deep learning model* (Goodfellow, Bengio and Courville 2016, 6).

The layers within DNNs are divided into input, hidden and output layers (fig. 5). The *visible layer* or *input layer* receives the data that is put into the system, which in the case of image processing refers to the pixel values of the image being put into the DNN. The *output* layer is the result given at the end of the process. In between the input layer and the output layer, there may be one or several *hidden* layers of neurons within the DNN. It's also noteworthy that the number of connections may vary between the various layers. To say that a layer is *fully connected* means that every neuron in that layer is connected to every neuron in another layer of a NN.

2: Backpropagation involves feeding information from the loss, or cost, back through the network during training. This is used to derive the gradient, which may be used to identify various critical points in the output of the network, and to adjust the network according to such thresholds.

What makes deep learning especially useful is that it enables each hidden layer in a DNN to extract increasingly abstract features from input data (Goodfellow et al. 2016, 6). This enables DNNs to extract hierarchies of information, building concepts upon one another to develop complex representations. To illustrate this idea, imagine that each successive layer of a DNN builds on the information of the previous one. Simple representations may be learned in some layers, such as visual patterns among a small group of pixels, which are then combined to detect more complex patterns and, ultimately, categories of images.

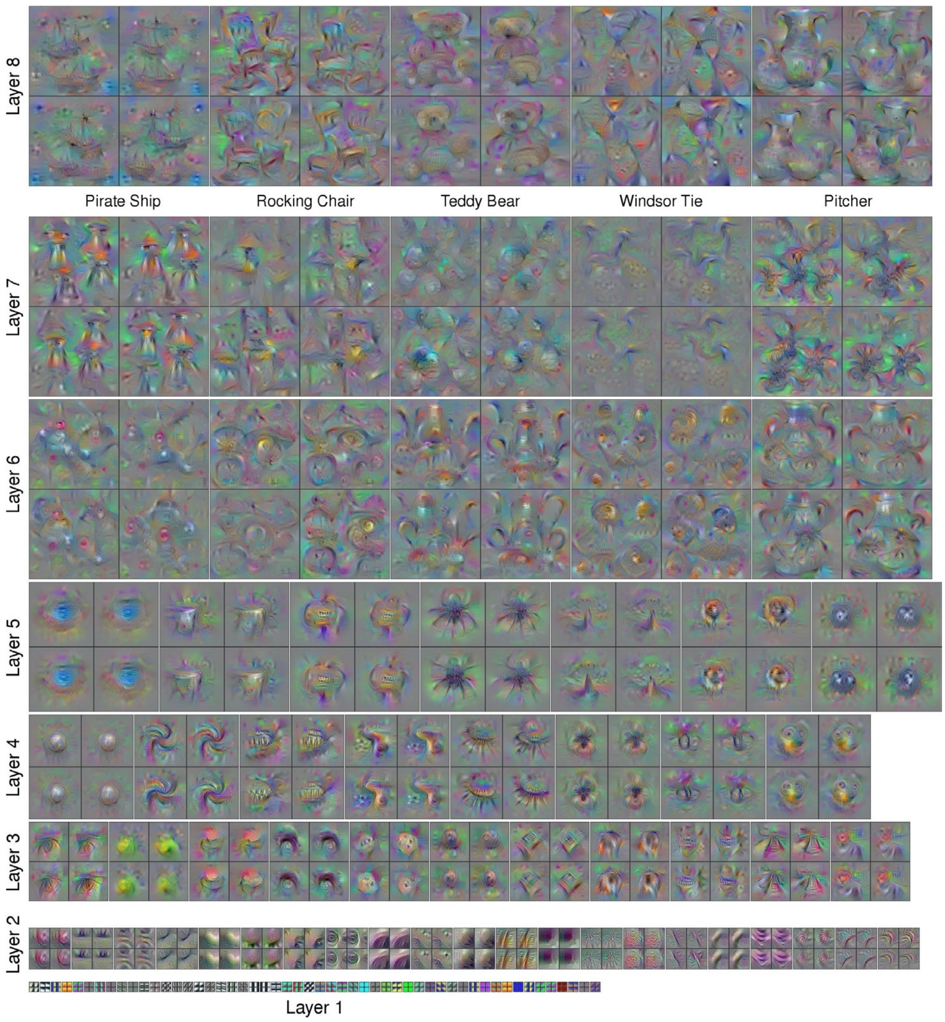



**Fig. 6:** Examples illustrating deep visualisation. *Deep Visualisation Toolbox* (Yosinski et al. 2015).

Because of the fact that the intermediary layers of a DNN may be hidden, it can be difficult to understand the processes which go on between input and output. Addressing this problem, *Deep Visualisation Toolbox*[3] (Yosinski

3: This is an example of a deep convolutional neural network (CNN/convnet). CNNs use parameter sharing, enabling “the same feature (a hidden unit with the same weights) [to be] computed over different locations in the input. This means that we can find a cat with the same cat detector whether the cat appears at column i or column i + 1 in the image.” (Goodfellow, Bengio and Courville 2016, 254) et al. 2015) (fig. 6) visualises the way in which DNNs function in a particularly understandable way by showing the activations of the neurons in each layer. It is thereby possible to see how each neuron is attuned to a different kind of feature. For example, a given neuron may learn to pick up horizontal, vertical or diagonal lines, or particular colour combinations, becoming activated when they are present in an image. In combination, these enable images to be analysed, with the activations become more fine-tuned from one layer to the next, moving upwards in fig. 6. It is also visible in some cases that these activations display a vague resemblance to their respective image class.

Common terms for describing the accuracy of ML models are the *loss*, or *cost*, of an algorithm. These indicate a measure of how well a model is suited to the performance of a given task. During training, the model is adjusted in relation to its loss with the intention of improving (i.e. minimising) this score. This means that in the case of *Deep Visualisation Toolbox* (Yosinski et al. 2015), the model would be improving at performing its objective (i.e. correctly predicting the labels of new examples) and therefore receiving a better score for performing that task. What results from this process of training is a trained model capable of distinguishing particular patterns in data that enable it to perform a given task with a high degree of accuracy. In the case of a discriminative task such as image categorisation, this would mean that the model may be used to effectively categorise new images. The overall score at the end of testing gives an indication of the accuracy of the algorithm — how well it was able to learn a representation of the example data.

In order to train a learning algorithm to correctly produce images that fit into a particular class, or category of images, it is necessary to provide the algorithm with a controlled set of examples fitting the characteristics of what it is expected to produce. This is referred to as a training *dataset*, which may be composed of *natural images* or *generated images*. This differentiates, respectively, between "image(s) that might be captured by a camera in a reasonably ordinary environment, as opposed to a synthetically rendered image, a screenshot of a webpage, etc." (Goodfellow, Bengio and Courville 2016, 550). Natural images offer a particular challenge for ML systems, enabling them to be tested on real-world image data, such as digital photographic images. Generated images give increased control over the composition of a training dataset, enabling many images fitting particular parameters to be produced.

Many image databases now exist, covering categories such as faces, fingerprints, everyday objects and many others. For example, the well-known MNIST database (LeCun, Cortes and Burges 1998) (seen on the left side of fig. 2, p. 31) consists of handwritten digits. Introduced in 1998, it remains a commonly-used image database. Its relative simplicity, involving only 10 image categories and low requirements in terms of resolution, makes it suitable for performing simple tasks and for demonstrating the basics of ML.

Image datasets have increased in size over time, from datasets containing hundreds of examples in the 1990s, to thousands of instances in the 2000s. ImageNet (Deng et al. 2009), for example, is an openly accessible, widely used dataset of more than 14 million images at the time of writing. It contains more than 20,000 different categories of labelled images. This has to do with a number of factors, including increased processing power and other resources devoted to ML, as well as the transmissibility and open-source material facilitated by the internet. The increased availability of high quality example images has been useful for ML applications due to the fact that training typically requires many examples, often in the thousands, as well as saving the time-consuming work to preprocess images.

### 1.3 Adversarial Approaches

Several aspects of an ML system's design may affect its overall performance. For example, a small group of low-resolution images of random objects does not give sufficient data to learn from and is therefore inadequate for the task of training a model to generate high-resolution images. A sufficient quantity of high-quality training examples is therefore necessary in order to train a model to perform accurately. For example, the production of Anna Ridler's (2019a) *Mosaic Virus* required the artist to painstakingly photograph 10,000 tulips to create a substantial amount of training data (p. 122).

The composition of a training dataset can be another factor which affects an algorithm's accuracy at performing a task. Datasets are often homogenous in factors such as size, shape and composition so that those factors do not have an influence on the outcome of training. Failure to properly prepare the training data may throw off the results, causing a model to incorrectly focus on aspects of an image that are not desired. Errors may also originate from aspects of training datasets, which may unintentionally throw off the results, which is discussed later in relation to built-in bias (p. 127).

While ereror is generally to be avoided, situations of error are also an important aspect of ML for the purpose of measuring a system's accuracy, and often to better understand its inner workings. For example, *adversarial approaches* aim to trigger errors in ML systems and can be used for a variety of different purposes, including genuine malicious attacks seeking to compromise an ML system and attacks employed for the purpose of testing and even strengthening a system by identifying its weaknesses.

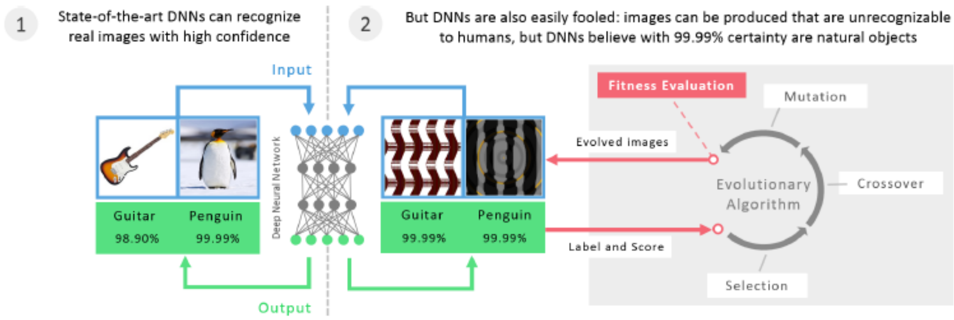



**Fig. 7:** Diagram showing image classification of real images (left) and fooling images (right). "Deep Neural Networks are Easily Fooled" (Nguyen, Yosinski and Clune 2015).

Noteworthy examples of adversarial approaches include the "One Pixel Attack" (Su, Vargas, and Kouichi 2017) (fig. 8), a 3D-printed turtle classified by ML algorithms as a rifle (Athalye et al. 2017) and a paper entitled "DNNs are Easily Fooled" (Nguyen, Yosinski and Clune 2015) (fig. 7). In each project, researchers demonstrate that an otherwise successful algorithm can be caused to make classification errors when given adversarial examples. Such *fooling images* are generated with the intention of appearing as a different class of image to humans than they are classified by an algorithm.

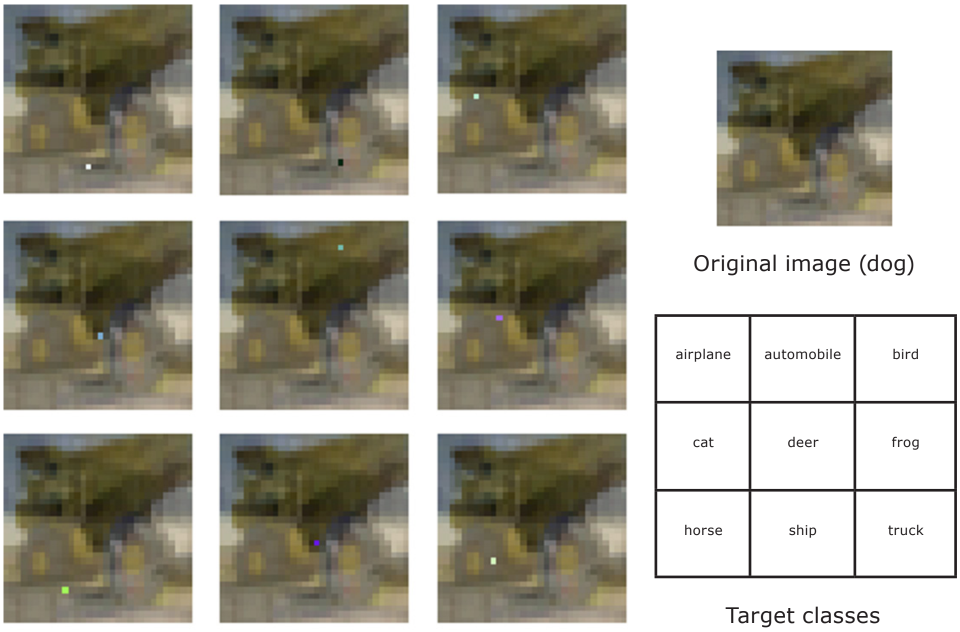



**Fig. 8:** Examples showing image classification of an image (right), in which one pixel has been modified to cause it to be misclassified as 9 different target classes. “One Pixel Attack for Fooling Deep Neural Networks” (Su, Vargas and Kouichi 2017).

Fooling images often play on the gaps between how images are perceived by humans and the way in which data is processed by an ML system. Human vision accommodates and compensates for visual noise in ways in which many CV systems are ill-adept, making this a potent weak spot to exploit. This kind of logic is used in many adversarial approaches, including the one-pixel attack (Su, Vargas and Kouichi 2017). While the alteration of a single pixel in an image may not be a significant hindrance for human viewers, it can mean the difference between two different image classes for a computer.


**Fig. 9:** Unintelligible reCAPTHCA (outonlimbs.com 2012).

The Completely Automated Public Turing test for Telling Computers and Humans Apart (CAPTCHA; reCAPTCHA) (von Ahn et al. 2008) is an important and familiar example of the instrumentalisation of differences between human and machine visual processing. This strategy involves the implementation of tasks that are easy for humans to perform, but which are difficult for computers to perform. This includes, for example, the distortion of images of text, which aim to remain readable to most humans, but which rendered the same images illegible to most computer systems at the time. reCAPTCHA has been a successful gatekeeper technology to limit access to websites to human users and not bots, for example, and has become an iconic fixture of the internet.

What is interesting about reCAPTCHA, in this respect, is that it relies upon the interplay between the interpretive abilities of humans and computers, neither of which are fixed. The creators of reCAPTCHA explicitly acknowledge the continual improvement in computational systems' ability to perform such tasks as image identification by emphasising their focus on the abilities of "current technologies" (von Ahn et al. 2008). Yet in spite of this insight, the reCAPTCHA system fails to acknowledge the diversity of human ability to perform the tasks presented to them by reCAPTCHA. This is especially evident in more recent versions of reCAPTCHA, which have also become difficult for humans to solve (see fig. 9).

The divide between the visual tasks performed by ML systems and human vision is made especially apparent in the case of adversarial examples. Many artists have seized upon this aspect of errors of interpretation performed by ML, including Adam Harvey (2017), Zach Blas (2016), Trevor Paglen (2017) and Hito Steyerl (2013), who have each worked with the issue of computers failing to decipher human faces (pp. 88–91). In each of these artists' projects on this topic, provocative, adversarial approaches are adopted as a way of visualising the inability of machines to perform visual processing tasks in the same way that humans see.

## 1.4 Generative Adversarial Networks

Introduced by Ian Goodfellow et al. in 2014, generative adversarial networks (GANs) have proven to be especially successful at the generation of believable photographic digital images. For this reason, GANs have become an influential approach employed by many artists and computer scientists working with graphical media. The GAN is a central ML architecture applied currently in the artistic use of ML, as well as being the primary technique explored in the cases covered in this thesis. This section introduces the technique, relevant examples and several variations on GANs.

GANs involve two distinct parts: a generator and a discriminator. These are often described metaphorically as opponents playing a game against one another to discern “real”[4] images (from the training dataset) from “fake” images (which have been generated). In this scenario, the generator produces sample images with the goal of fooling the discriminator. The discriminator, on the other hand, is a binary classifier, which must discern whether sample images come from the generator or from a database of existing sample images.

The generator and the discriminator are each given a score based on their ability to perform their respective task. Each time the discriminator succeeds in correctly identifying a sample image as real or fake, its loss score is reduced. But each time it incorrectly labels an image, for example identifying a fake image as real, its loss increases. Likewise, the generator’s loss is decreased each time it succeeds in having the image it generated classified as a real image, and its loss is increased each time it fails to fool the discriminator.

The generator is given a noise input, from which it is to generate an image. The discriminator is given the fake sample images from the generator and real sample images from the dataset in an unpredictable order. This is important because if the training images and the generated images are given to the discriminator in a defined pattern, the discriminator could simply learn the pattern in sample images occur in order to determine which images are training images or generated images.

Gradients are then adjusted based on these positive and negative rewards to the generator and discriminator, and the weights of the network are adjusted accordingly. As the network is trained, the generator improves at its task of generating images that can pass for images from the training dataset. And on the other side, the discriminator improves at its task of correctly identifying images as either having been generated or having come from the set of sample images. As the discriminator and the generator each get better at their respective tasks, the more accurately the images produced come to more accurately reflect the attributes of the dataset employed.

Each part of the network gets better at its respective aim, while also increasing the challenge to its counterpart. The closer the generator gets to producing an image that will fool the discriminator, the higher the score it receives, and the better the discriminator gets at correctly identifying images, the higher its score will be. Over time, the two parts of the network tend to con-

4: It’s important to note here that the distinction between “real” and “fake” images is not an inherent quality of the images, but is instead relative (or positional) within a system. For example, the real images in a given system may be generated, not natural, images, but they are distinguished from the fake images within the same setup by how they are used.

verge towards the optimum, in which the discriminator cannot distinguish between real and fake sample images. The GAN's structure enables each part of the network to help adjust the other, making it a powerful approach to unsupervised learning. This makes GANs capable of producing highly realistic images from unlabelled data, as opposed to more supervised approaches, which can be more brittle and reliant on labels.

The approach outlined in the original 2014 GAN paper may now be seen as rudimentary compared to today's capacities, but it has nonetheless had a very influential effect within the field of ML, as well as image creation within art. More recent projects have outpaced the GAN approach that was first introduced, in terms of resolution, parameters and ultimately, effectiveness. This is also related to an overall increase in the computational power of ML systems, which has improved dramatically in recent years.

Other projects that have expanded upon GANs in notable ways. For example, a deep convolutional GAN (DCGAN) (Radford, Metz and Chintala 2015) incorporates convolutional layers. The benefit of this approach is that it allows unsupervised learning to be performed on image datasets, making it possible to work with unlabelled data.

*BigGAN* (Brock Donahue and Simonyan 2018), enables the production of larger images than had previously been produced using GANs. In the paper in which *BigGAN* is introduced, new techniques have proven to be effective for working with higher resolutions of images than had previously been experimented with. In addition to resolution, BigGAN also allows the implementation of more parameters than the previous state of the art, giving the images produced in this fashion higher levels of visual complexity.

Due to the technical possibilities available, it is becoming difficult for human viewers to differentiate between real images and those which have been generated using ML. *This Person Does Not Exist* (Wang 2019), for instance, is a well-known example involving the use of a *StyleGAN* (Karras, Laine and Aila 2018) is another variation of GAN architecture, which applies the idea of style-transfer to GANs. The highly photorealistic images of human faces, which are displayed on *thispersondoesnotexist.com* (Wang 2019) demonstrate the deceptive power of generative algorithms. Other related examples include deepfakes (p. 123), visualisations using "synthetic training data" (Forensic Architecture 2017) (p. 121) or visually-ambiguous generated images which are not neatly individuated into conceptual classes of images (melip0ne 2019) (p. 120).

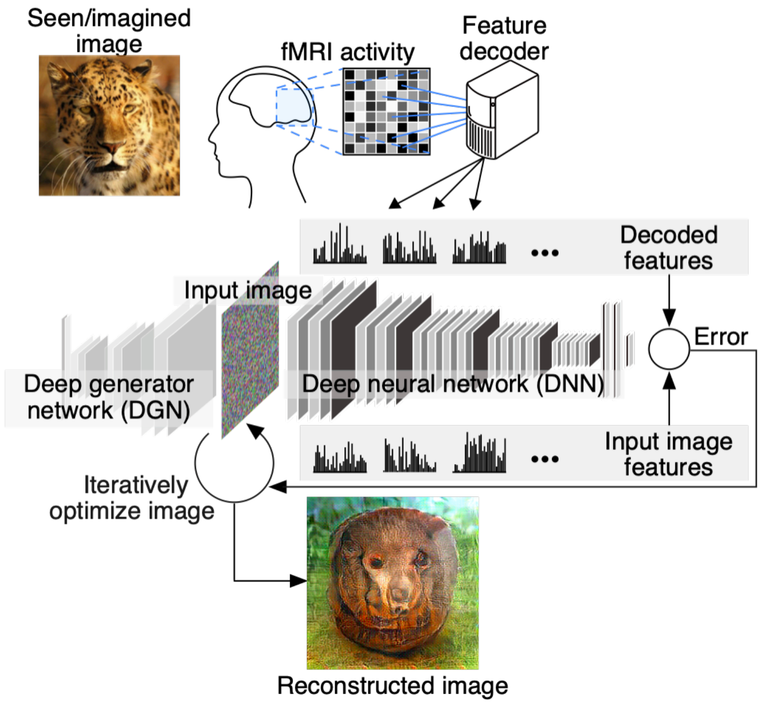



**Fig. 10:** Diagram of deep image reconstruction process. (Shen et al. 2019).

An approach called *deep image reconstruction* (Shen et al. 2019) is used by Pierre Huyghe (2018) in his work *UUmwelt* (p. 106), which incorporates functional magnetic resonance imaging (fMRI).[5] Deep image reconstruction is based on the idea that recordings of subjects' neural activity while they think about a previously seen image or object may be decoded and recomposed into a representation of that mental image.

For each image produced in *UUmwelt* (Huyghe 2018), an individuals' brain activity is recorded in two phases: while subjects look at images from different categories, one at a time; and while they are told to think about each item they just saw after receiving a cue word.

Next, the data is pre-processed and a DNN is then trained with the labelled fMRI data. The fMRI signals are smoothed to increase the ratio of signal to noise and feature extraction techniques are also applied. The "region of interest" (Shen et al. 2019) is identified using a DNN to establish the location of the visual cortex in subjects' brains, where the processing of visual information is concentrated. This allows the data to be more clearly interpreted, by focusing on signals from that isolated area of the brain which is related to processing visual information.

5: This technique involves the use of a combination of techniques including fMRI, a technique for measuring and visualising neural activity. It involves mapping out the location and intensity of blood flow in the brain, in which increased blood flow in one area indicates increased cognitive activity in that area.

The recordings of the subjects' brain activity, while looking at a set of objects and while thinking of those same objects with eyes closed, are labelled with the object associated with them. For example, recordings made while a person is looking at a picture of a cat and those recordings made while that same person thinks about the picture of a cat are both labelled with the category "cat". Neural networks are trained to match the data from the fMRIs to its respective category. Coarse-level classification, meaning classification based on more general types, is then applied. This means that the neural network learns to identify which one of the larger categories a signal corresponds to. After an image category has been identified, a finer-level classification is applied to recognise more specific object types.

In the final stages of the process of deep image reconstruction, the fMRI data is interpreted into the form of an image using a GAN. A DNN is used to generate an image from the fMRI data, matching it to learned representations from the training period. Finally, a trained GAN is used to reinterpret those images into more human-interpretable images.

## 1.5 Artbreeder Experiment

ML affords not only new methods but may also act as a complement to the creative process of producing images. For example, ML may be used to identify potentially useful areas for further exploration within a large *search space* of potential solutions. The fact that ML also has a tendency to produce unpredictable results (Lehman and et al. 2018) enables it to play a dynamic role in explorative image-making processes.

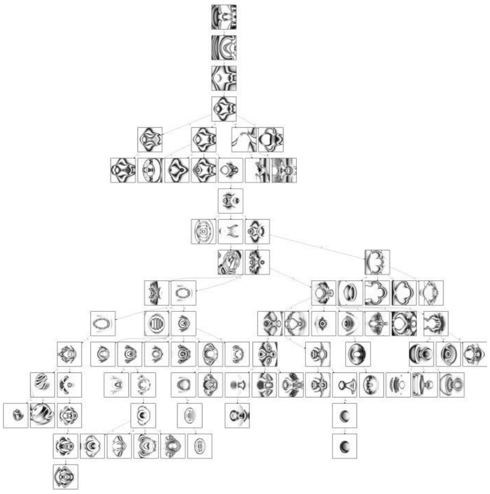


**Fig. 11:** Example of evolution using *Picbreeder.* (Secretan et al. 2007).

**Fig. 12:** Illustration demonstrating the mixing together of attributes of a Maltese dog with a bubble, using *Artbreeder.* (Simon 2019).

*Interactive evolution*, for example, applies the concept of biological evolution to computation. This may take the form of generating a group of example images, from which a smaller group is selected to *breed*, producing a new generation reflecting the qualities of the combined examples. A *fitness function* is employed to evaluate the outcomes' success at solving a given problem. *Artbreeder*[6] (Simon 2018) offers a useful example of interactive image evolution, building upon the simpler, more graphical approach of *Picbreeder* (Secretan et al. 2007) (fig. 11). The *Artbreeder* system enables images to be merged, combining selected image classes in various ways. This results in images that may have the properties of several distinct kinds of images, such as in fig. 12, in which images of a bubble and a dog are bred to produce an image that has attributes of each.

6: Formerly Ganbreeder.

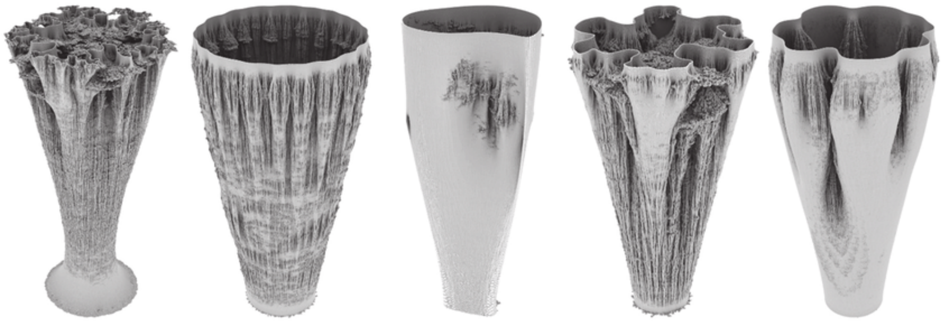


**Fig. 13:** *Five Vase Forms* (Andy Lomas 2017).

As a technique for image production, interactive evolution makes it possible to generate a set of outcomes and to fine-tune attributes of those outcomes in a non-linear fashion, offering a method for developing novel content in a relatively intuitive way. For example, artist and computer scientist Andy Lomas (2017) has employed interactive evolution to evolve and combine attributes of sculptural 3D forms in his project *Vase Forms* (fig. 13).

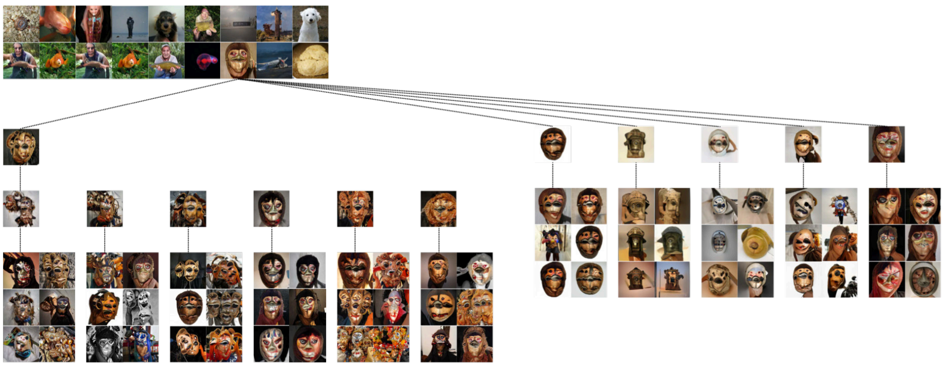


**Fig. 14:** Illustration of image evolution. *Artbreeder Experiment* (Lee 2019a).

In experimentation with *Artbreeder* (Simon 2018), I explored how human decisions may influence outcomes when using such a system to produce images. When using *Artbreeder*, one may only see one set of results at a time, meaning that one only has a partial idea of what might be produced, but this lacks breadth showing all possible outcomes that one might choose among. To get around this issue and to develop an idea of the diversity of images produced by the *Artbreeder* system, I gathered together all possible outcomes descending from an initial starting image over several generations. In so doing, I was able to visualise how an individual user's choices might change the final outcome from repeatedly "breeding" images to produce new "offspring" images. The result of this process is something akin to a family-tree of images from a starting image to its many potential outcomes, as generated using *Artbreeder*.

Fig. 15: Images evolved using *Artbreeder,* detail of fig. 14. *Artbreeder Experiment.* (Lee 2019a).

Fig. 16: Images evolved using *Artbreeder. Artbreeder Experiment.* (Lee 2019a).

What I found was disappointing is that the *Artbreeder* system demonstrated a lack of diversity among the different lineages of images. While there was some variation among the different sets of images, the overall aesthetics of what was produced tended toward certain similar sets of traits. From several attempts at experimenting with this system, I found that it was possible to produce interesting outcomes by using *Artbreeder* as intended. While this does not offer the user a comprehensive overview, it does enable a more explorative approach than painstakingly considering all possible outcomes associated with a given starting combination.

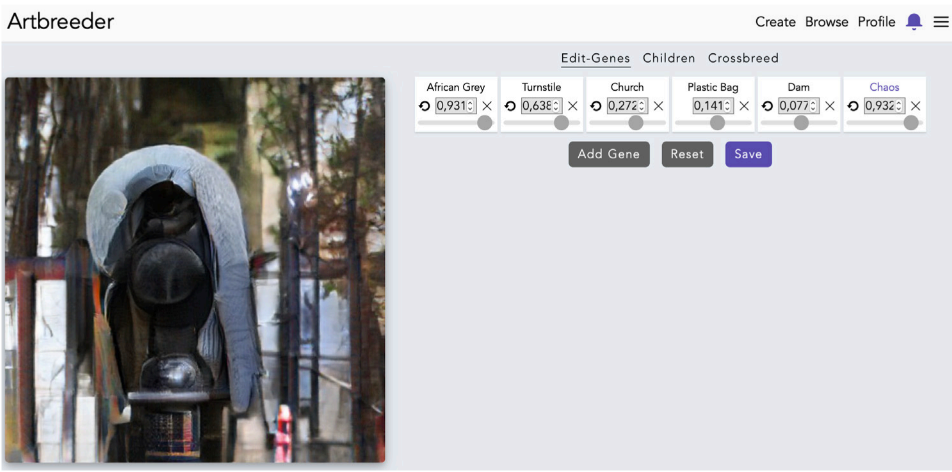



Fig. 17: Images evolved using *Artbreeder. Artbreeder Experiment.* (Lee 2020).

The *Artbreeder* system has subsequently changed to enable users greater control on the genome used for producing images. One may combine, for example: african grey parrot; turnstile; church; plastic bag; dam; and chaos, to produce the image above (fig. 17). This affords users greater control to over the process than was possible previously, combining various kinds of images together.

## 2. Algorithmic Image Processes

### 2.1 Algorithmic Procedures

Due to the increasing influence of machine learning (ML) algorithms, it has become commonplace to refer to visual media as being *algorithmic*, but it is not always clear what qualities this refers to. Jamie Bianco (2018, 24) defines an algorithm as "a set of modular or autonomous instructions – in execution — for the doing or making of something". The algorithmic character of a process or artefact may thereby be understood as tied to the method employed, as opposed to being bound to a particular technology, such as the digital computer. As such, algorithmic qualities can also be found in instances that vastly predate contemporary digital imaging technologies involving the use of digital computers and ML.

It has been argued by Hoelzl and Marie (2015) and Kittler (2007) that algorithmic processes are linked to much older — even ancient — forms of image-making, employing the systematic use of mathematical principles in the creation of images. Such artefacts may involve quite different technological means than those employed in current examples of algorithmic media, but nonetheless share important modalities in common with them. In such cases, the algorithmic quality of images has little to do with the highly automated tasks performed by present-day digital computers but rather refers to the manual execution of algorithmic processes. The word "algorithmic" may thus apply to simple analogue processes performed by humans, such as the systematic use of geometry and optics to inform the creation of images, instead of being limited to those that are performed by machines.

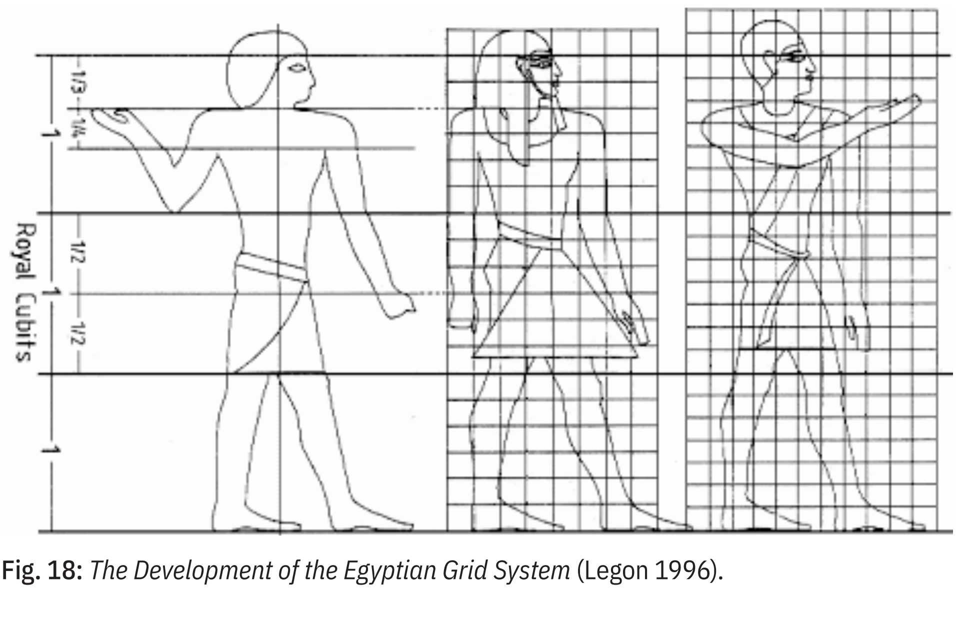
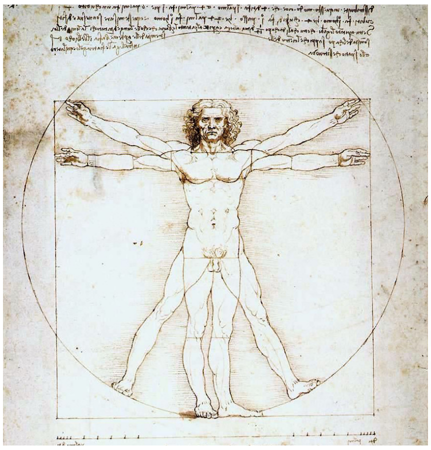



Fig. 18: *The Development of the Egyptian Grid System* (Legon 1996).

Processes related to the use of algorithms today are recognisable in the creation of images according to strictly formalised rules and procedures, such as the geometric canons of representation employed in ancient times (Hoelzl and Marie 2015). For example, in ancient Egyptian art, canonical representation constrained the proportions of visual components in accordance with standardised units, such as the *cubit*[1] (c. 3000 BCE). Based on the length of the forearm from the elbow to the middle fingertip, the cubit is an *anthropometric*[2] system of measurement, which has been used in 2D compositions, as well as in architecture. Though the cubit entails a level of variability according to whose body is used as the basis of the measurement, it lends an internal consistency to constrain the relative size of visual elements within a composition when used systematically.



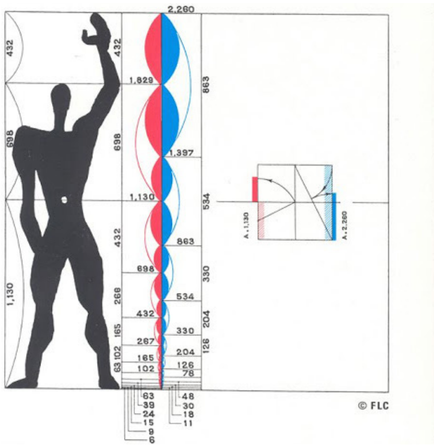



Fig. 19: *The Vitruvian Man* (da Vinci 1490).

Fig. 20: *Le Modulor* (Le Corbusier 1945).

A similar system of geometrical canon of bodily proportions is laid out by Vitruvius (c. 30 BCE) in *De architectura*. Best known for its use by Leonardo Da Vinci (1490) in his *Vitruvian Man*, Vitruvius's system is effectively written out as instructions for the execution of a drawing of the human body. The size of each component part is defined relative to each of the other components: for example, the length of the face is one-tenth of the height of the body, the length of the open hand is the same as that of the face, and so on. (Vitruvius c. 30 BCE). The proportions laid out by Vitruvius were informed by observation of human proportions, in combination with ideas concerning what were to be regarded as "ideal" proportions, according to the golden ratio. A modern example of a similar approach is the *Modulor* system of Le Corbusier (1945) (fig. 20), which has also been applied as a tool in design and

1: The cubit was a a standard unit of measure in ancient times. Several variations of the cubit have been used across different cultures and time periods.
2: Referring to the systematic measurement of the human body.

architecture. These proportional systems demonstrate the capacity of the same formulaic quality to be applied not only to 2D compositions but also to the design of dimensional structures and the built environment.

Another poignant use of algorithmic instructions and internal proportional relations within an image can be found in the history of cartography. *Geographia* was an atlas of the known world at the time it was written by Ptolemy in c. 150 CE, compiling data from many sources into a written index of coordinates. Ptolemy provided detailed instructions for others to be able to interpret his coordinates and to draw out maps from that data. This was an answer to the laborious task of copying maps by sight alone, by making it easier to faithfully reproduce a map by relying on data. The fact that the Ptolemaic maps could be transcribed as an index of mathematical information also proved critical to their survival through history. Any existing maps from Ptolemy's era have been lost, but the detailed and systematic coordinates transcribed by Ptolemy made it possible for the maps to be plotted centuries after the atlas was originally composed.

When the Ptolemaic atlas was translated from Greek to Latin in 1407, it upended the methods of medieval cartography. Instead of basing the relative size of countries on power relation, which was the cartographic tradition at the time, *Geographia* employed a system of coordinates that catalogued the locations of geographical features and their proportional spatial relations. This gave rise to a greater degree of accuracy in mapmaking by basing depictions of the world on real-world measurements, as opposed to in accordance with ideological notions regarding the relative importance of the territory represented. Not only did this have an aesthetic impact, but it also changed the maps' referential relation to the world, presumably rendering the resulting maps more accurate as navigational tools (see figs. 21–22).

Rigorous attention to real-world measurements in Ptolemy's — and to a certain extent, Vitruvius's — data-based images thereby portended the development of a view of the world based on mathematic and scientific principles, as opposed to the more ideologically-based and symbolic forms of representation that had been in place up to that point. In contrast, the proportional relations of ancient Egyptian art do not necessarily correspond to the relative size of objects in the real world and instead rely on a highly symbolic form of representation. In addition to making images more compatible with how they are perceived in real life, the Ptolemaic atlas also demonstrates a shift from the view of images as representations of the world to images taking the form of a dataset (Hoelzl and Marie 2015), "a structured collection of data" (Manovich 2001, 218).

**Fig. 21:** *Latin world map according to Ptolemy's 2nd projection, the first known to the West* (Germanus 1467).

**Fig. 22:** *Ebsdorf world map* (Ebstorf c. 1235).

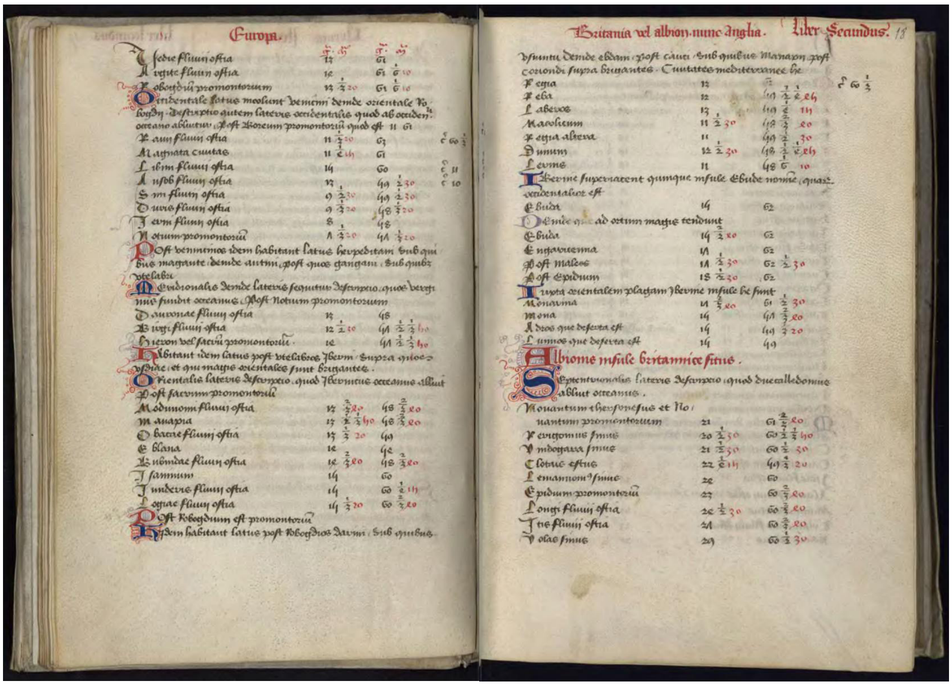



Fig. 23: *La Cosmographie de Claude Ptolemée* (Clavus 1411—1426, 42-43).

> ... every text, even a very abstract one, means, in the last analysis, an image. (Flusser 2002, 64)

Both Vitruvius's and Ptolemy's methods allowed precise instructions for a visual depiction to be formulaically transcribed in written form so that, by following the instructions, one can produce the prescribed image. One may resize, reinterpret or misinterpret the instructions for creating an algorithmic artefact, with virtually endless possibilities. The potential for multiple readings from a given set of instructions adds to our understanding of the algorithmic image, making a case for a mutability usually reserved for thinking about computational media. This makes it possible for images to be read or to be expressed in more than one way, across a variety of different media. For example, the instructions for a given algorithmic image may be performed manually, using simple equipment, or it may be interpreted into digital form.

The capacity for data-based images to be transcoded between various forms recalls the quality of conceptual artworks, such as Kosuth's (1965) *One and Three Chairs*, to exist between a variety of different media. The work presents three instantiations of the concept "chair": a wooden chair; a picture of the chair; and a printed dictionary definition of the word "chair". It illustrates how a concept may maintain continuity between its various instances, which may take on a diversity of material forms. Applying this understanding to images separates the physical instantiation of the image from its conceptual form.

This highlights the unique temporal and material qualities found in algorithmic media. If we are to think of Ptolemy's atlas as an index of image data, an algorithmic image (each map) exists in unarticulated — virtual — form until it is drawn out in the form of a map. Echoes of the same idea can be found in Lawrence Weiner's (1968) statement that "the piece need not be built", allowing the possibility that an artwork — or image — may exist in a state of latency without ceasing to exist. *Latency* (Cubitt, Palmer and Tkacz 2015, 16), refers to the temporal suspension of image processes as they are transferred from one form to another. In digital photography, says Cubitt (2018), the term latency refers to the temporal delay between the reception of photons onto a digital camera's sensor and their subsequent transmission in the form of digital signals. This offers an interesting example, in which latency involves the material processing of light into digital code by the sensor of a digital camera.

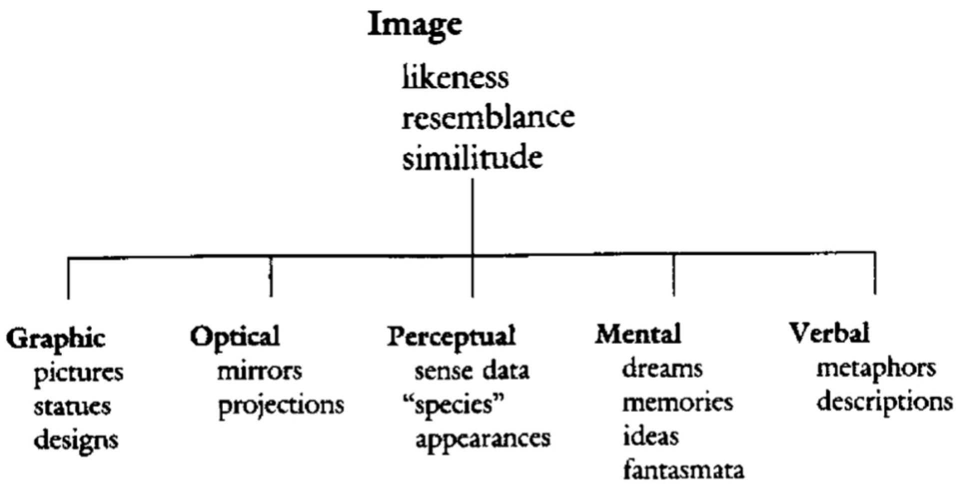



**Fig. 24:** Family tree of images. (Mitchell 1986, 10).

According to Mitchell's "family of images" (1986, 9) (fig. 24), images are understood as transcending the specificity of any single medium. They may be instantiated in various ways across various media, whether taking on a graphical, optical, mental, or verbal form. For example, a *verbal image* (Mitchell 1986, 27) such as a written description of an object may conjure a *mental image* (Mitchell 1986, 13) of that object in the mind. We thereby understand images to have a degree of consistency between instantiations, whether in pictorial, written, spoken or other form.

A contemporary example which demonstrates this idea well is the *File Room* by artist group Ardnode (2017) (fig. 25), in which data in various different file formats (including images and sound) is translated into a series of 3D printed objects. The capacity for data-based images to be articulated as dimensional forms helps to stretch our understanding of images beyond solely 2D surfaces, as they are traditionally understood.

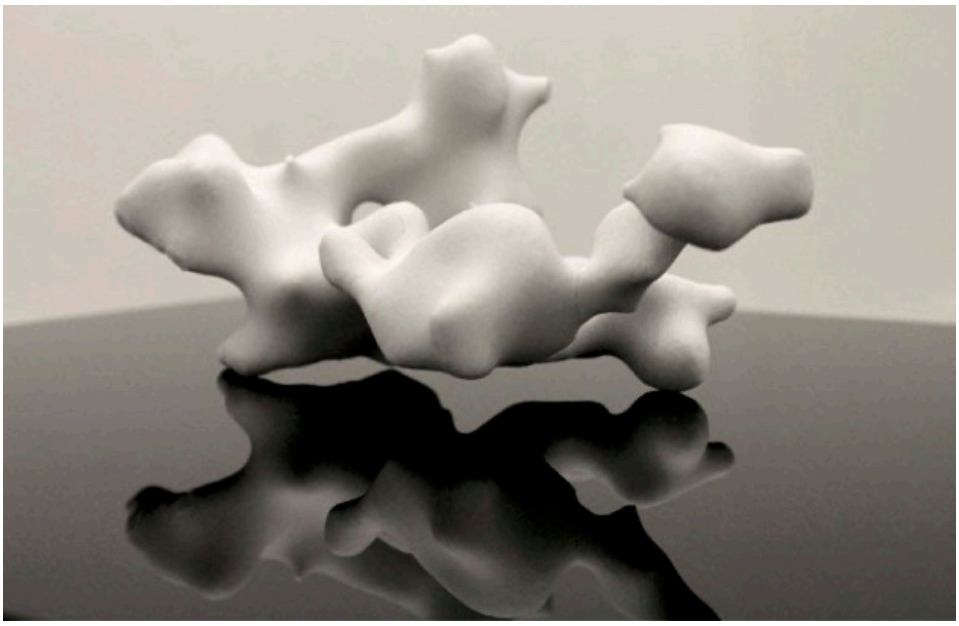


**Fig. 25:** 3D printed sculpture. *File room (*Artnode 2017).

Modalities and concepts related to the analogue algorithmic processes covered here have also been explored within contemporary art contexts, often involving the construction of an image according to a programmatic set of instructions. Such approaches have been especially notable in the work of conceptual artists, in which ideas and interpretive processes take precedence over the specific visual or material qualities of an artwork.

Vera Molnár, an early proponent of computer art, explored the artistic and aesthetic potential of computational processes in paintings created according to what the artist referred to as an imaginary machine, or “machine imaginare” (1960). Following algorithmic instructions to execute the paintings, the artist took on the conceptual role of a computer — one that (or whom) computes. The computational dimension of these works is attributable, thus, not to a digital computer, but to computation as a procedure enacted in order to produce the work.

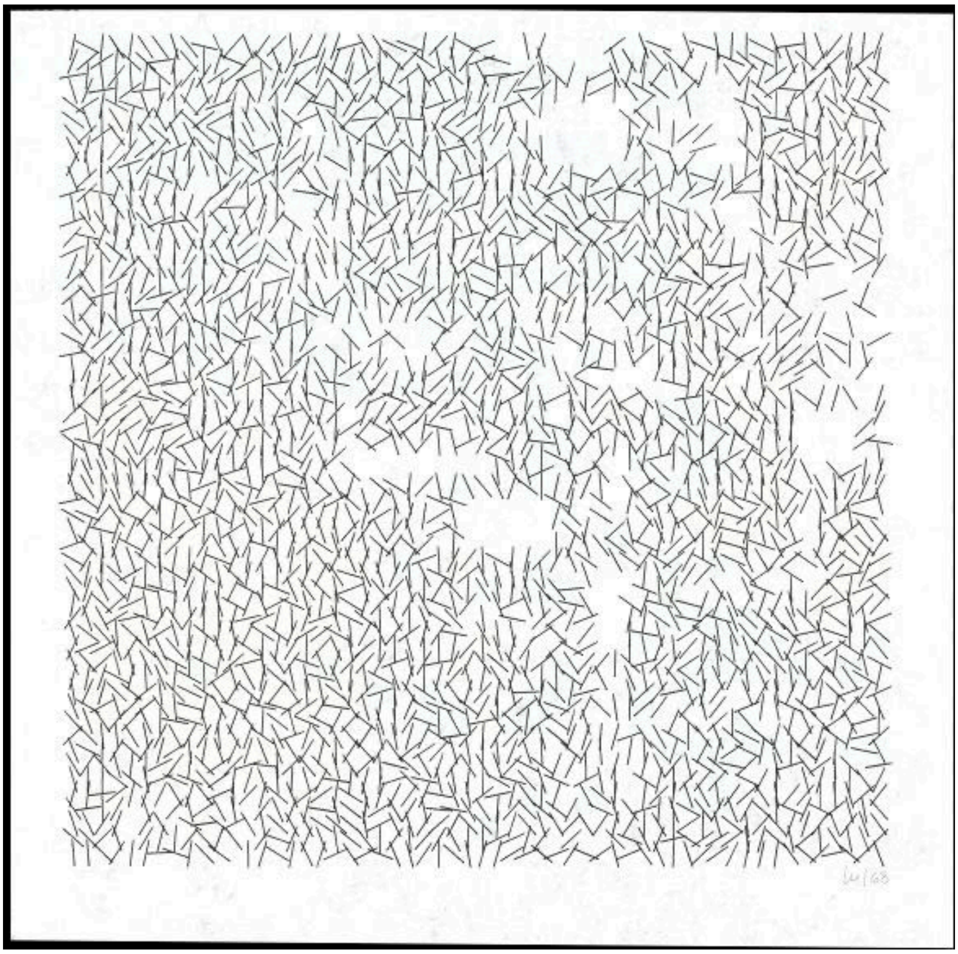


Fig. 26: *Interruptions* (Molnár 1969).

Many other artists have worked with highly structured processes and sets of instructions to be interpreted or orchestrated, often entailing the deliberate forfeiting of a degree of agency, deferring it either to other people, machines or the orchestration of an algorithmic procedure. Important examples of performative, instruction-based works include the chance-based compositions of John Cage,[3] the *Instruction Paintings* of Yoko Ono (1964) and On Kawara's *Date Paintings* (1966–2014).

3: Described in his lecture "Experimental Music". (Cage 1957)

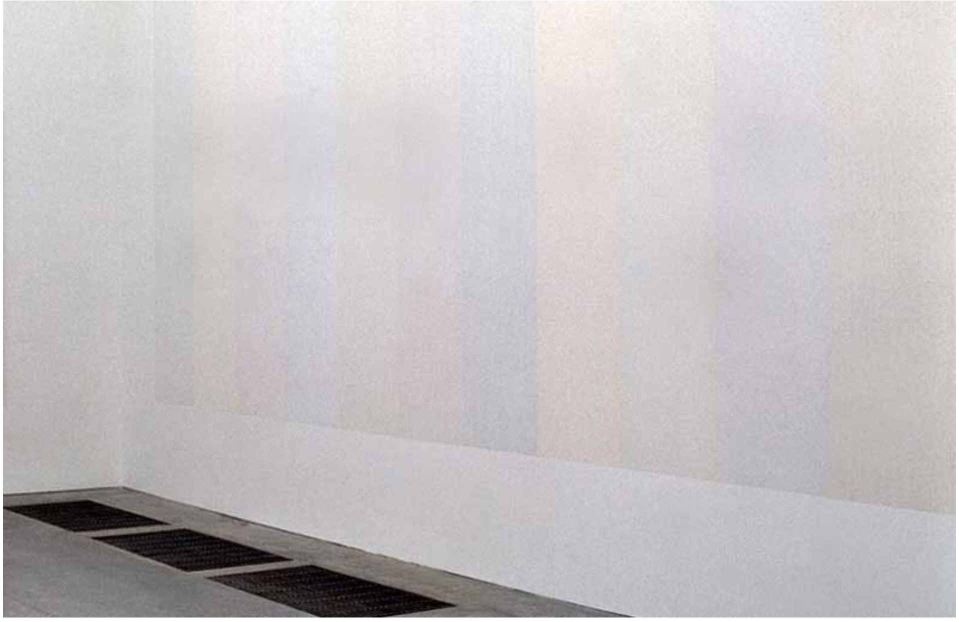


**Fig. 27:** “A Wall Divided Vertically into Fifteen Equal Parts, Each with a Different Line Direction and Colour, and All Combinations”. *Wall Drawing 47* (LeWitt 1970).

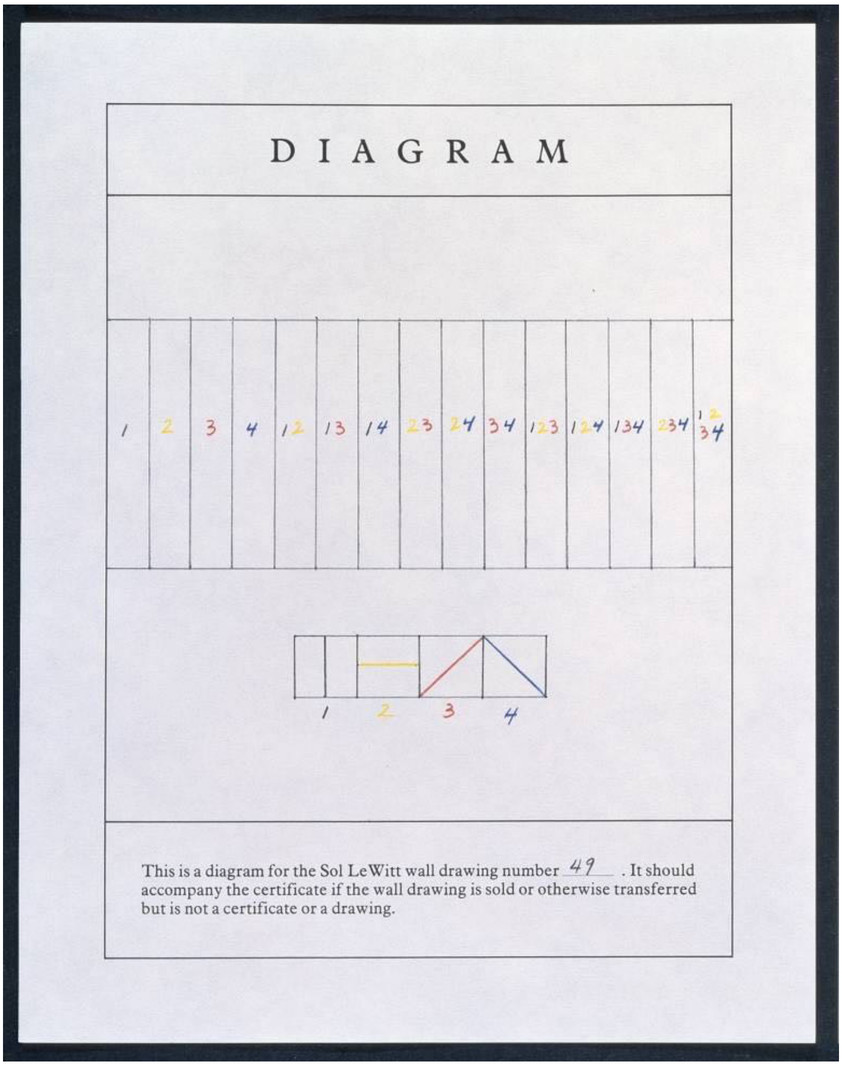



**Fig. 28:** *Diagram for Wall Drawing 49* (Sol LeWitt 1970).

The instructional wall drawings of Sol LeWitt (1968) (figs. 27–28) engage with variability of execution within a set of strictly defined constraints by giving sets of instructions that may be interpreted differently each time they are enacted.

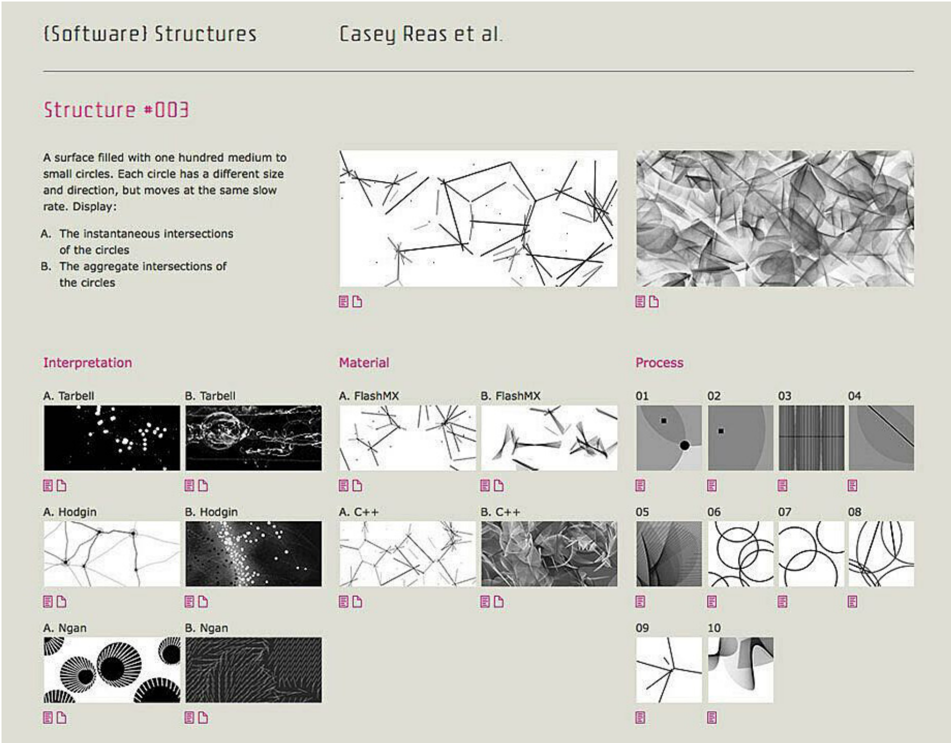



**Fig. 29:** *{Software} Structures* (Reas et al. 2016).

LeWitt's wall drawings have been reimagined by Casey Reas, a generative artist and co-founder of the Processing programming language, in the work *{Software} Structures* (2016). In Reas' version, custom software creates drawing-like, dynamic patterns and structures based on LeWitt's instructions.

Marcel Duchamp's final work, *Étant Donnés* (1946–1966) (figs. 30–31) relies on a program of instructions written explicitly to be carried out by someone other than the artist upon the event of his death. Considered to be Duchamp's magnum opus, the artist specifically gives licence to others to produce a work according to a meticulously composed instruction manual. The built installation engages visitors to peek through a set of peepholes in a door, which offers a highly constrained view of an intricate diorama. Framing the gaze thus, the field of view is constricted and the dimensional space of the work is effectively flattened into a plane. In this sense, it may even be argued that this artwork can be thought of in terms of an expanded image, exceeding the image surface in similar fashion to how *expanded cinema* (Youngblood 1970) stretched the medium of cinema beyond the screen. Duchamp's engagement with the game of chess in the later years of his life is also anecdotally relevant here, expressing a preoccupation with algorithmic systems, related to game-like structures in procedural art.

Figs. 30–31: *Étant Donnés* (Duchamp 1946–1966).

*Procedural practices* (Carvalhais 2016, 145) have been employed by artists, using a great variety of different techniques and systems to draw influence from processes and systems. This has a strong historical relation to the development of *generative art*, exploring the potential for autonomous systems to in turn create emergent behaviour. Chance-based, or *aleatory*, procedures, such as the roll of a die or the use of cards have been popular techniques of using randomisation to direct artistic decision-making, bringing together variability within a set of constraints.

Early experimentation with such ideas can be found in the Surrealist notion of *automatism* (Bauduin 2014), which has been an especially influential analogue approach to artistic creation through generative processes. In the wake of WWI (1914–1918), many artists sought to combat the rationalism they blamed for the devastating consequences of the war by seeking to evade their own consciousness within the artistic process. To this end, highly systematised, rule-based techniques were used to surrender creative control by handing over agency, intentionality, or control to a process, machine or system.

*Recombination* (Carvalhais 2016, 146), rearranging components of an initial starting state, is another important modality of many generative approaches. One example of this is the *cut-up method*, used by Dadaists (c. 1922) and which Brion Gysin and William S. Burroughs are well known for using in the 1950s and into the 1970s. The cut-up method is a process in which an initial object — a text or image, for example — is cut up at random and rearranged by the artist, influencing the creation of a new work from the rearrangement of an existing one.

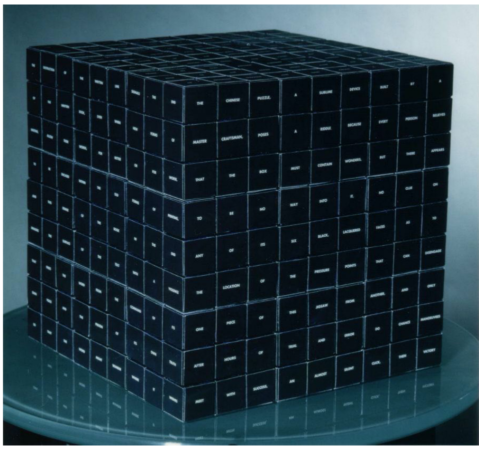


Fig. 32: *Bibliomechanics* (Bök 2012).

Fig. 33: *Cents mille milliards de poèmes* (Queneau 1961).

Automatic literature and visual art had a particularly strong connection to this modality, the influence of which is tangible in the “bookish artware” *Bibliomechanics* by the experimental poet Christian Bök (2012). The work engages aleatory processes in a novel way, stacking together 27 Rubik’s Cubes into a writing-machine of sorts. All sides of the resultant oversized Rubik’s Cube are black, but each facet bears a word on its face. A reader may reassemble the cube at will, revealing a sentence 81 words long. Rearrangement of the cube allows for 4.3 x 627 permutations, though not all of them are sensical.

This work has been referred to by the poet as a 3D version of *Cents mille milliards de poèmes* by Raymond Queneau (1961), who was a member of the avant-garde literature group OuLiPo. Known for their approach, which involved the imposition of highly constrictive sets of formal rules, the members of OuLiPo sought to discover new patterns and structures, effectively expanding the potential possibilities of literature. *Cents mille milliards de poèmes* is a book composed of 10 sonnets, in which the pages are cut into strips bearing one sonnet each. By flipping the pages, readers may combine the sonnets as they wish to produce a new reading of the text, with 1014 possible outcomes.

## 2.2 image machine / machine image

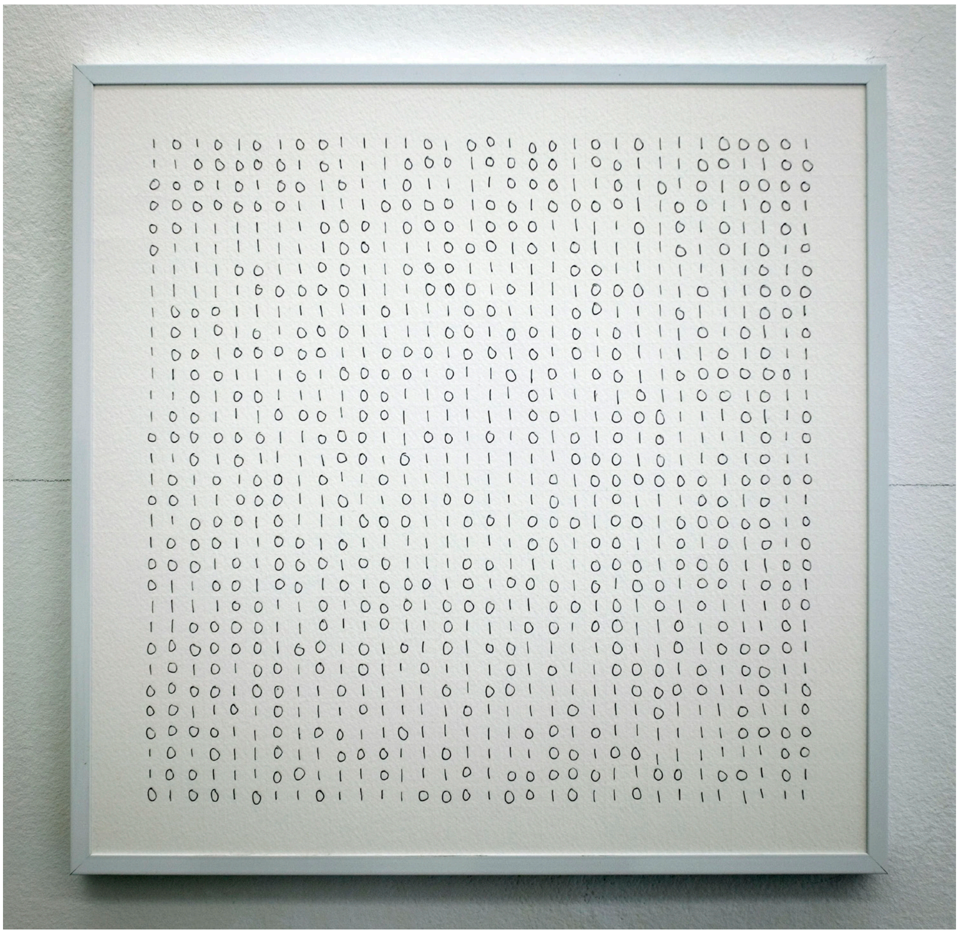
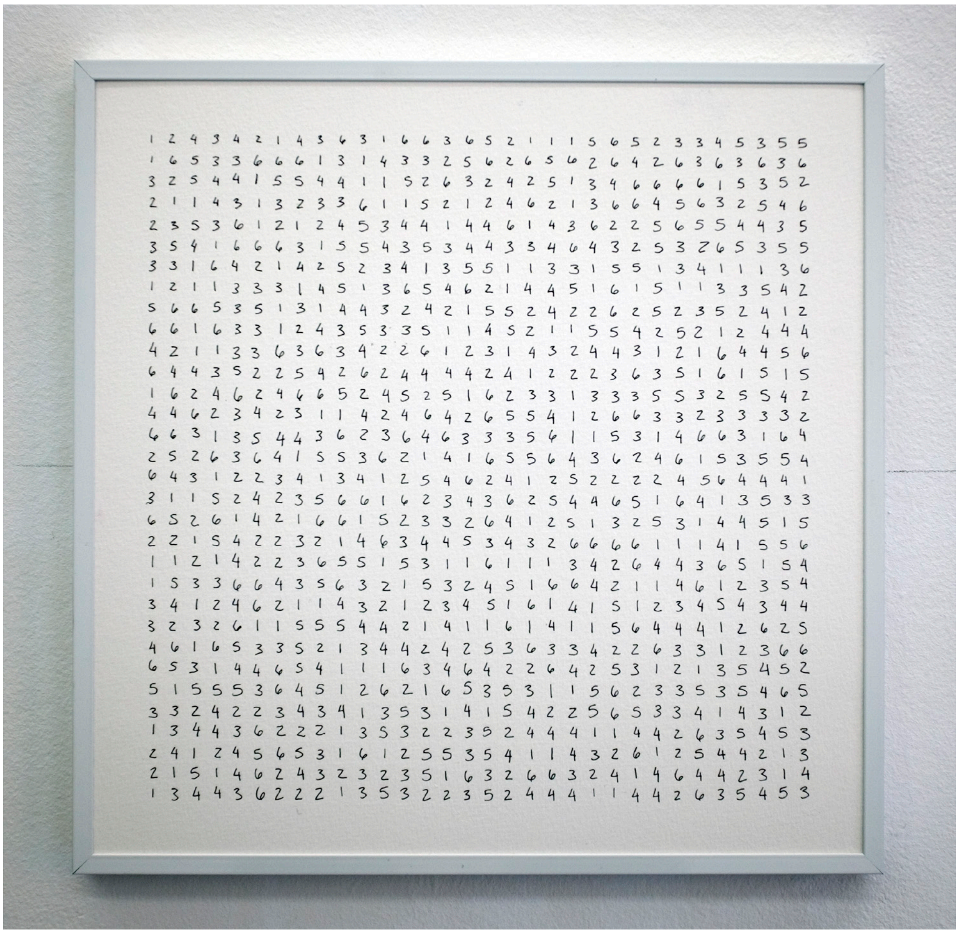


**Fig. 34–35:** *Image determined by the flip of a coin.* (Lee 2019c).

Taking a close view of image generation itself, I developed a series of drawings, *image machine / machine image* (Lee 2019c) that reflect the algorithmic qualities of image production. The work seeks to break down the digital image to its most basic level: pixel values, which are determined by algorithmic processes. To that end, I explored several modalities discussed thus far in this research, seeking to build up from simple analogue, aleatory processes, toward those that are more complex, automated and involve ML. Each "post-digital image" (Cox 2019) is composed of a hand-written matrix of numbers representing the pixel-values for an image that may be produced by entering those values into a computer.



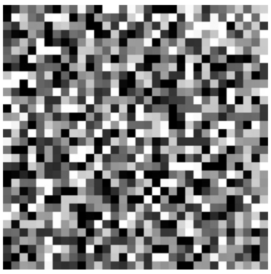
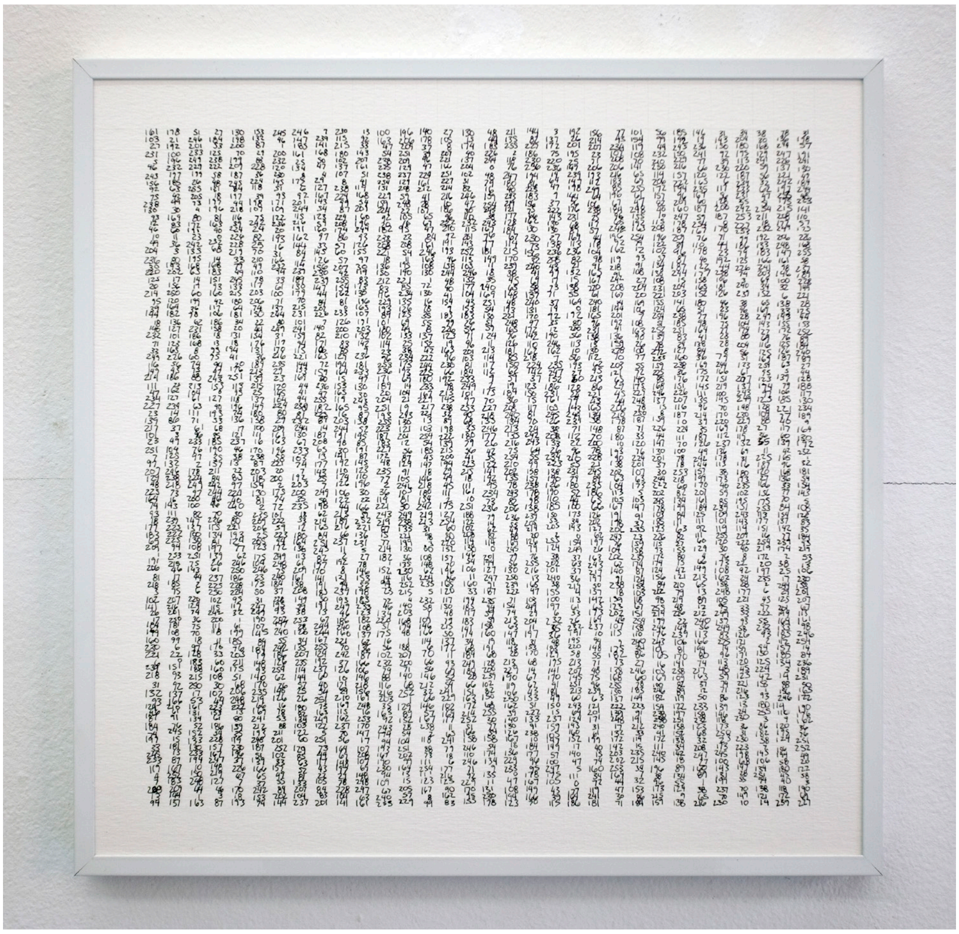


**Fig. 36–37:** *Image determined by the roll of a die.* (Lee 2019c).

The series plays upon the idea of transcribing a computational image as a form of writing, rather than drawing. What is made visible to the viewer is akin to instructions which could be employed in the production of images. The pixel values of each image have been determined by processes involving various degrees of complexity. Each image is composed of a 32 x 32 grid, each cell representing a pixel. Each pixel value in the images is arrived at using one of five procedures: the flip of a coin; the roll of a die; the RAND function in Microsoft Excel; averaging pixel-values from a database of images; and using Google Reverse Image Search to retrieve a new image based on the previous image in the series and translating it into pixel values.



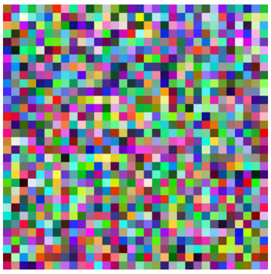
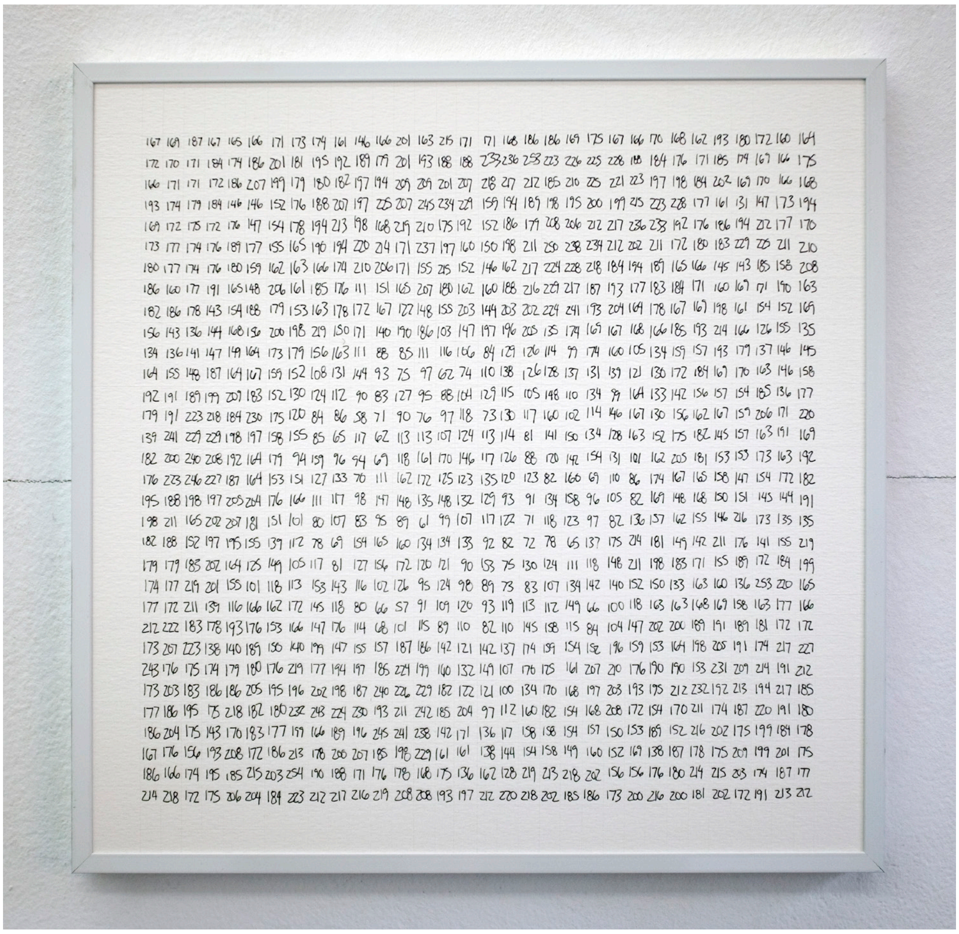


**Fig. 38–39:** *Image determined by RAND function in Excel.* (Lee 2019c).

Although the images in the series were generated through the use of unpredictable algorithmic processes, I found that there is a fine balance between producing novelty and interesting outcomes. While the progression from very simple procedures toward those that are more complicated provided more interesting results than those employing randomness alone, unpredictability on its own proves insufficient to make images that could qualify as art or even sustain more than rudimentary critical discussion. Though it has been argued that ML has the capacity to consistently produce surprising results (Lehman and et al. 2018), this does not necessarily offer much to artistic production other than tools to direct exploration.



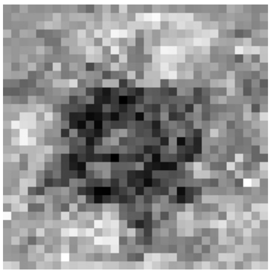
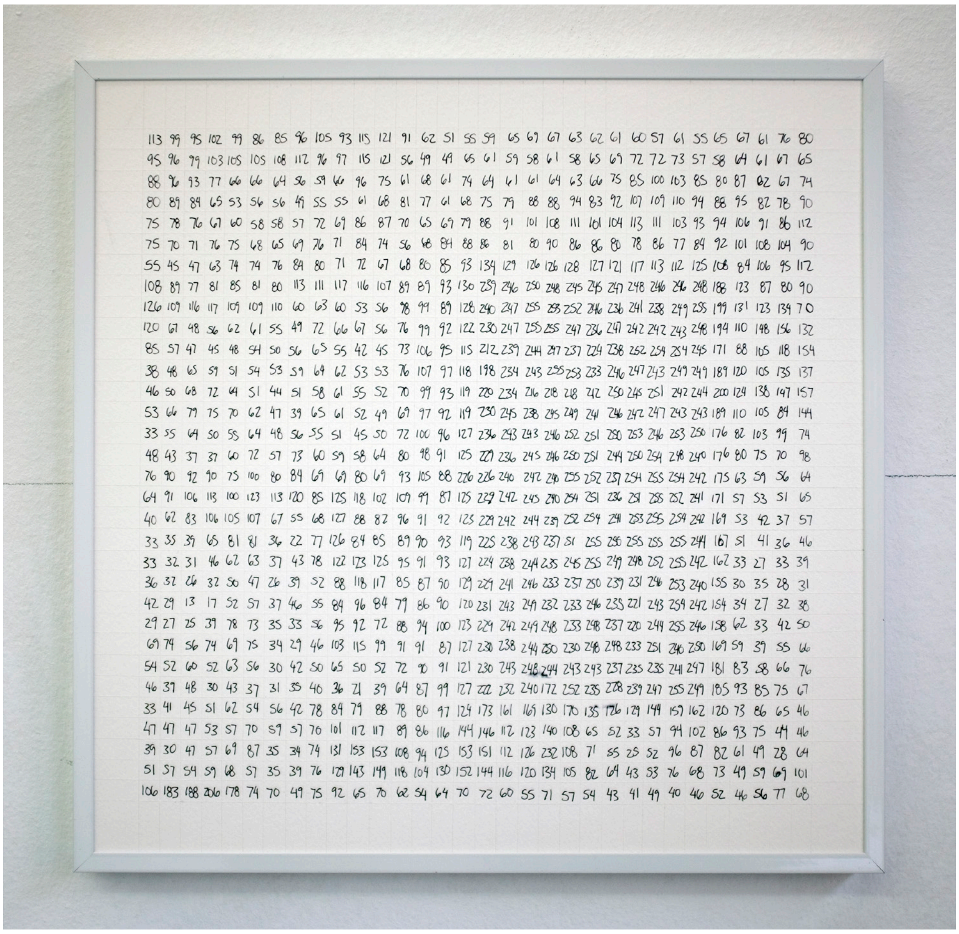


**Fig. 40–41:** *Image determined by averaging images together.* (Lee 2019c).



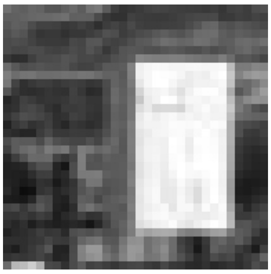


**Fig. 42–43:** *Image determined using Google reverse image search on previous image in series.* (Lee 2019c).

## 2.3 Softimage

In addition to the procedural quality discussed thus far, the use of scientific methods and apparatus to produce images offered the potential to make images more compatible with human visual perception and to automate production processes. The systematic implementation of optical principles had a number of effects on how images are viewed — both in terms of their aesthetic qualities, and in terms of their significance. The design of visual technologies also had the effect of mediating and repositioning the human gaze, which is a recurring theme in many examples covered in the continuation of this thesis.

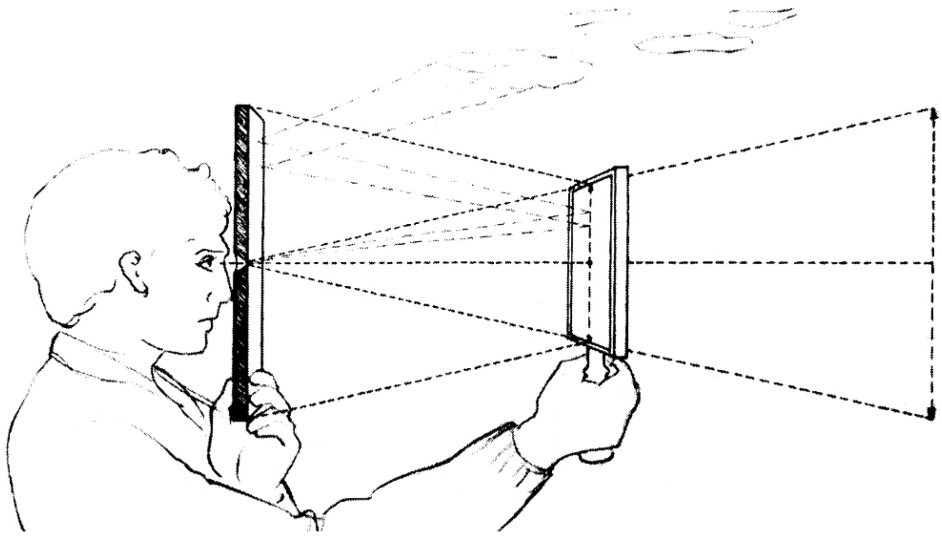


Fig. 44: *A Reconstruction of Brunelleschi's First Experiment* (Parronchi 1964).

Artists were likely aware of optics in much earlier periods than the Italian Renaissance (c. 1400–1600), but Filippo Brunelleschi (c. 1415) is credited for its systematic implementation through the technique of linear perspective. Like the implementation of image composition according to sets of instructions already covered here, linear perspective is connected to algorithmic processes in image production because it enables the internal proportions of images to be structured according to geometric principles that are governed by optics. In addition to his perspectival techniques, Brunelleschi also designed an apparatus that could be used to verify the accuracy of perspectival images (fig. 44). The apparatus involves creating a peephole in the centre of an image, through which one may view a mirrored reflection of the image and thereby compare it directly with the real object or view that it is intended to represent. This seemingly simple intervention is in fact rather momentous, as it places the viewpoint directly at the interstices between the viewer, the image and the world.

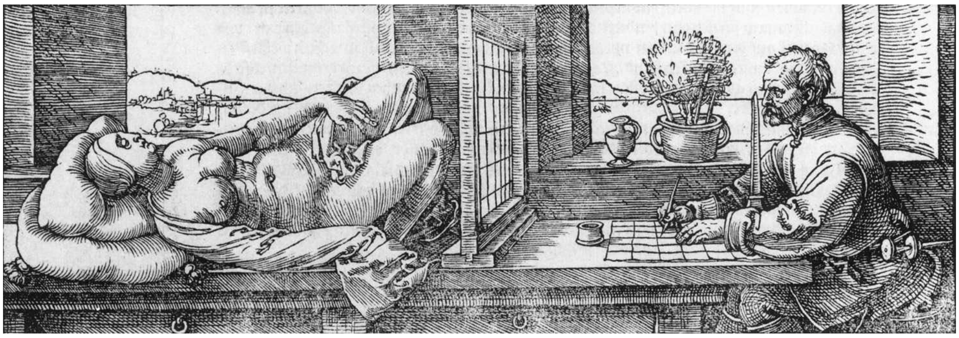


Fig. 45: Woodcut showing Alberti's optical device. *Draughtsman Drawing a Recumbent Woman* (Dürer 1525).

Leon Battista Alberti (c. 1425) expanded upon Brunelleschi's techniques with his own inventions, including the use of a gridded window or frame, which imposed a matrix on what was viewed through it (seen in fig. 45). The grid acted as a guide for observational drawing or painting, which enabled artists to better estimate spatial relations between elements in a composition. Alberti's window device also had the effect of flattening the field of view, enabling unseen parts of objects, such as those hidden behind other objects, to be inferred rather than visually represented in the resulting image. Imposing a pictorial plane upon representations of the world thereby gave them greater compliance with human optical perception. It's also noteworthy that the segmentation of the image that occurs in Alberti's window technique bears a resemblance to the pixel grid of the much later digital image.

Fig. 46: *Detail of Altarpiece from Thuison-les-Abbeville: The Ascension* (Unknown c. 1490–1500).

The implementation of optical principles through the use of linear perspective, optical apparatus, and the flattening of the pictorial plane enabled spatial relations and proportions to be constrained by geometry and optics, more so than subjective interpretations of appearances. The impact of such techniques is especially apparent when contrasted with the relative compositional flatness of pre-perspectival paintings, which often contain blunders such as misunderstandings of foreshortening, as in fig. 46, or the then-common practice of portraying babies with the bodily proportions of adults, only smaller in scale.

The tendency towards naturalistic representation, which optical media played a part in, signalled a change from images playing a largely symbolic role, as previously discussed to images based upon the mediation of the perceptual experience of the world through science and technology. Through the previously described examples, we see how visual technologies mediate perception and pictorial representation of the world in a way that is interlinked. The devices of Brunelleschi and Alberti demonstrate quite directly how technical apparatuses mediate relations between the viewing subject, an object of representation and the production of an image. Not only does each device mediate the point of view, but its use also aids the viewer in adjusting their image to be more compatible with what is seen. In this way, the technical mediation of human perception comes to modulate the production of images.

As a result of these changes, it became possible to make images that had greater correspondence with human spatial perception, giving images a more realistic illusion of depth. *Optical media* (Kittler 1999) thereby caused the appearance of the image to become more compatible — even visually interchangeable — with the world around it. By holding a mirror to reality (in a direct sense in the case of Brunelleschi's mirror technique) images started to become more faithful reflections of the qualities of optics so that the eye perceives two-dimensional surfaces as equivalents of real-world three-dimensional objects.

Though at first primarily focused on text, the invention of moveable type (c. 1455) contributed to the mass-replicability of texts, as well as images. In comparison to older forms of print media, such as lithography or wood-cuts, moveable type allowed the recombinant rearrangement of components within a composition. This accelerated the production and reproduction of print media, facilitating the "Gutenberg Revolution",[4] a considerable increase in the number of books printed in Europe, which in turn led to increased dissemination of knowledge.

4: This refers to how the invention of moveable type by Johannes Gutenberg in 1455 enabled the mass production of print media.

*Reproducibility* (Benjamin 1935) rendered mechanically produced images commonplace in comparison to the scarcity of one-of-a-kind, manually produced images. Technically reproducible images were therefore seen as inferior to painting, due to their deviation from existing conventions that treated art objects as singular entities. Seriality was already possible before the mechanisation of printmaking processes, but higher degrees of automation took its possibilities to greater degrees.

Mechanised printing expanded upon older forms of printmaking processes, which were also capable of producing multiples, albeit more slowly. In addition to the acceleration of image production and its replicability, the modularity of moveable type also treated textual components and images interchangeably. This made images mechanically programmable, for example by treating a text-based composition as a single image, composed of modular elements. The punchcard loom is another interesting example that predates the digital computer, in which a mechanical program enables a machine to produce specific visual patterns — in this case, in the weaving of cloth.

The advent of photography, too, caused the incorporation of automated mechanical processes in such a way that Vilém Flusser (1983, 26) likened the function of the camera to the performance of a mechanical programme. In yet another incremental shift, optical relationships were embedded in the image-making process through the execution of the camera's mechanised procedure. Like the printing press, the camera also enabled the production of multiple images from a single photographic negative. We may thereby think of the analogue, in-camera photographic process as akin to encoding the source-code of images into film through the performance of mechanical algorithmic processes.

Though the processes involved in digital photographs are quite different from those of analogue photography, they nonetheless have certain algorithmic modalities in common. In digital photography, images are also created using highly systematic digital processes that are performed automatically by the camera. Digital cameras now also often include ML-informed features such as face detection, autofocus, lighting correction or the addition of digital lenses or filters, making the end result the product of a host of algorithmic processes, not all of which are necessarily visualised in the final image.

> Consider the case of Wikipedia, a singular (data) image produced by thousands and thousands of end-users on their laptops. (Galloway 2011, 94)

The digital computer's capacity to function as a *metamedium* (Kay and Goldberg 1977, 394) has made it possible to simulate a great array of previously discrete forms of visual media, computationally. Digital imaging thereby adds to many of the qualities of earlier forms of image production, further increasing their speed, potential for mass dissemination and the degree of automation involved.

Expanding upon the issues raised by Benjamin (1935) regarding reproducibility of print media, the same quality in digital images may also have an impact on their materiality. Multiples often lack the material as well as the symbolic worth of materials traditionally associated with traditional art forms like painting or sculpture, such as the use of lapis lazuli and gold, or oil on canvas, as opposed to the use of common materials, such as prints on paper. The highly technologically mediated, algorithmically governed and participatory context of the internet (since Web 2.0, c. 2000) takes this even further. It enables the possibility to access, duplicate and disseminate images at will. As a result, it has become commonplace to distribute digital media without regard to legal restrictions and to treat images as forms of intellectual property rather than visual or physical objects.

Hito Steyerl (2009) describes the fleeting quality of digital artefacts through her concept of the *poor image* (1), which she says prioritises speed and transmissibility over traditional views, which champion resolution and scarcity. Poor images place value on an image's performance, rather than the complexity of its composition, prizing communicability over bandwidth. Sarah Kember and Joanna Zylinska (2012) similarly emphasise a transition "from thinking about 'new media' as a set of discrete objects" (1) to understanding media predominantly in terms of processes of mediation and remediation (8).

It's relevant to note that there is an interpretive dimension in decoding the instructions of transcribed visual data into the form of an image. Though it is possible to transcode an image between many different forms, it is reinterpreted at each stage of that transformation. In their examination of data compression, Ingrid Hoelzl and Rémi Marie (2015, 63–80) demonstrate how a digital image may be compressed and decompressed or transcoded between file formats with variable degrees of faithfulness to the original image file. Compression artefacts visually attest to this in Thomas Ruff's

(2007) *jpegs* series, whereby images are visibly degraded through a process of repeated compression and decompression.

The relation between images and data in networked media has been explored explicitly in relation to search engines in Mohammed Salemy's (2016) curatorial project and associated publication, *For Machine Use Only*. Examining the human-machine cooperation that occurs on an ever more frequent basis in current algorithmic media, Salemy invited a group of artists and theorists to submit original works that reflected upon Google's reverse image search. Image search renders images and search terms effectively interchangeable, except that for each query, there may be multiple results.

While algorithms have influenced pictorial representation for a long time, the responsiveness of algorithmically-determined visual phenomena aims toward a reactivity that is unprecedented in other forms of media. Not only are algorithmic images, themselves, highly variable, but so too are the modes of access that determine their display. What becomes visible in browsers, apps, search engines or social media platforms is often dependent upon vast amounts of previous data, both from the individual viewing the content and from millions of other users.

The reading of a media artefact can thereby be seen to be informed not only by its inherent properties but also by the modalities by which it is mediated. This means that not only are individual media artefacts subject to the influence of algorithmic procedures in the processes that have been used in their production, as well as that of the interfaces through which they are accessed, in their display and transmission: it also points to the fact that networked media is not uniform, and may show different things to different individual viewers at different times.

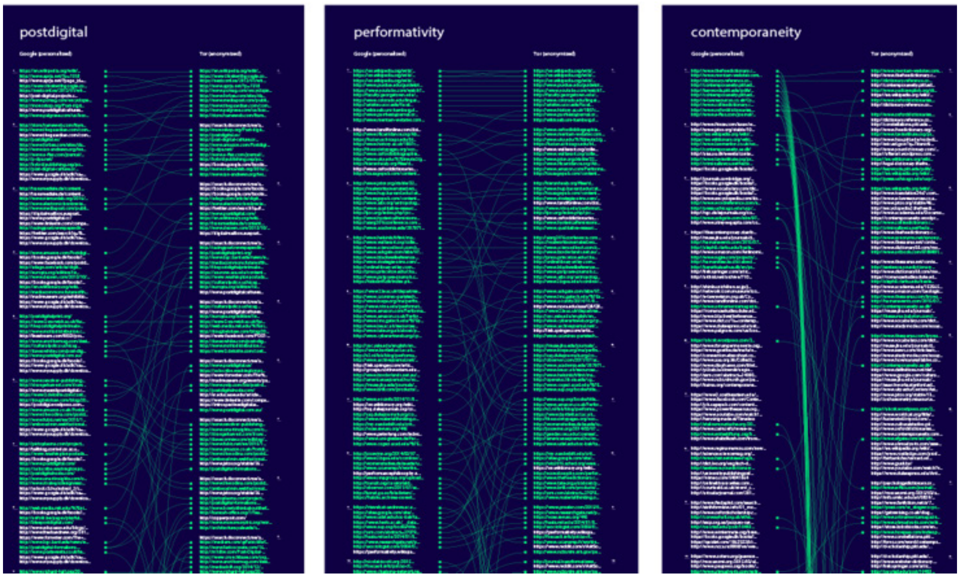



**Fig. 47:** Comparison of Google Search ‘personalized’ and Tor Browser ‘anonymized’ search results with keywords ‘postdigital’, ‘performativity’ and ‘contemporaneity’ Green represents ‘identical’ URLs. White represents ‘unique’ URLs. *Against a Personalisation of the Self* (Ridgway 2017).

Networked content is often algorithmically “personalised”, creating a profile of a given user based on past browsing habits, demographics, location and previously viewed content, as well as social connections to other users. In *Against a Personalisation of the Self*, Renée Ridgway (2017) examines how the personalisation of visual media lends itself to a high degree of variability in terms of what content is made accessible to individual users. This makes networked content highly contextual and subject to algorithmic processes that are often inaccessible to users. In her experiments, Ridgway compares the results displayed for an “anonymous” — or control — computer with search results that are given for a computer which has been “personalised”. In so doing, she demonstrates the lack of impartiality in networked media, given the algorithmic tailoring of results toward user profiles.

This also has to do with what has come to be known as “surveillance capitalism” (Zuboff 2019), in which the mass-collection of user data is implemented in coercive digital media practices in which algorithmic systems are used to track, monitor and monetise the behaviour of individuals. Not only has this led to privacy concerns, regarding the handling of users’ personal data, it also contributes to a feedback loop in which particular content is displayed based on previously viewed content. It also polarises discourse by siloing users into media bubbles in which they are grouped together with others with — presumably — similar media preferences or habits.

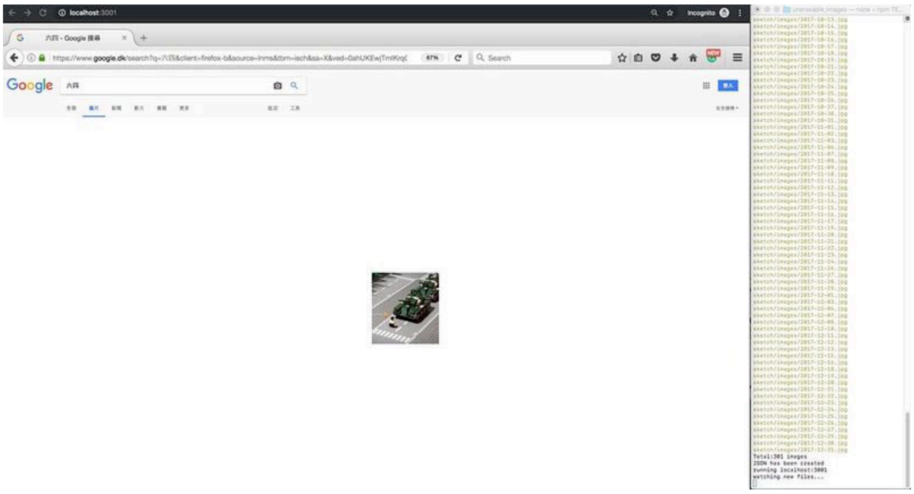



**Fig. 48:** *Unerasable Images* (Soon 2018).

Demonstrating the volatile nature of internet content, Soon's *Unerasable Images* (2018) documents the censorship in China of particular internet content related to the student-led Tiananmen Square Protest in Beijing in 1989. To produce the work, Soon conducted daily Google image searches for a particular search term, "六四" ("64"), a reference to the date of the protest. Documenting the results that appeared in the form of a screenshot, she then deleted all the resulting images except for a particular image of a Lego version of the iconic "Tank Man" photograph, the best-known image related to the Tiananmen Square protest. The original image shows a man standing in the way of a line of advancing tanks, which in this version is recreated out of Lego.

The reason for focusing on the reinterpretation of this particular image is that it has shown an ability to overcome the Chinese campaign of censorship of any reference to the protest, written or visual. The Lego tank man images, in contrast, disappear eventually but remain online longer than direct copies of the original image, which are taken down immediately. Reinterpreting images into unexpected forms thereby endows some visual content with a greater capacity to resist censorship than direct representations, because they can be more difficult to automatically detect. This and the previous example make visible how the mechanics not only of individual artefacts of visual media but also of their modes of transmission and visualisation, may be subject to algorithmic processes.

This focus placed on process and procedure has led to the development of alternative value systems for the appraisal of digital artefacts, fitting with Hoelzl and Marie's (2015) assertion that " the *algorithmic image* is no longer governed by algorithmic projection, but by algorithmic processing." (5) Rather than materially-fixed, stable objects, algorithmic processes reveal a tendency towards a lack of media specificity, which applies to digital images, and which is further expanded in current implementation of ML to perform similar visual tasks.

> "While the digital revolution erodes both the technique (geometry, projection) and the philosophy (transparency, truth) that underpinned it, the photographic paradigm seems to remain intact on the level of visual perception, so that today the photographic image occupies the entire field of representation as well as the one of vision." (Hoelzl and Marie 2015, 3)

Hoelzl and Marie's rethinking of the image, the softimage,[5] informs the perspective of this thesis. Not only does it enable us to understand the modalities particular to algorithmic media – new or old – but it also emphasises a connection to historical image-making paradigms which continue to shape discourse.

The images explored thus far in this chapter recall Manovich's (2001) principles of new media: *numerical representation*; *modularity*; *automation*; *variability*; and *transcoding*. As Manovich states, these tendencies are difficult to differentiate from "what new media is not" (49), not by definitively altering the defining qualities of images, but rather by expanding them incrementally. This brief overview of algorithmic qualities in images through the examples covered in this chapter demonstrates how the possibilities for producing various effects are built upon over time. This is not to say that image-making processes become inherently more complex over time, but that the abundance of visual technologies available is a marker of current media which may be contrasted with those of the past.

The implementation of algorithmic procedures in the production of images enables images to take on transmedial qualities, in which non-visual processes play an important role in addition to the visual properties of images. Many of the image-making processes discussed here consider the interrelation between objects, texts and images, and their potential to be enacted through various forms of mediation.

5: Hoelzl also uses the term "postimage".

# 3. Viewing Machines

> Later, owing to advances in automation, image makers became ever more superfluous, so that today fully automatic apparatuses produce, reproduce, and distribute images. Although this cannot be called "art" in the modern sense of the word, it is about powerful models of experience. (Flusser 2002, 128)

## 3.1 Machine Mythology

The highly automated processing of visual information exhibited in images produced using machine learning (ML) is often compared with the performance of similar processes by humans. Not only does this lend itself to metaphorical connections between biological vision and the interpretation of visual information by machines, but it also raises questions as to the autonomy of machines from human influence. The automation of image production processes has thereby given rise to ideas of images as a reflection of nonhuman agency and ability, or as being closer representations of reality as a result of the presumed autonomy — and therefore, it is assumed, objectivity — of technically produced images. In such cases, the role of machines relative to humans is often unduly diminished or overestimated.

The Industrial Revolution (c. 1760–1840) was marked by the automation of many production processes, including those of visual media. Mechanical apparatus enabled what had previously been laborious tasks to be performed quickly, easily and cheaply. As discussed previously (p. 69), this led to the devaluation of mechanically reproducible images (Benjamin 1935). Automation also had immediate ramifications for labour, allowing processes that had formerly been exclusive to manual production processes to be delegated to machines. The resulting cultural backlash against automation placed machines at odds with human ability. For example, in the Luddite rebellion (1812–1816), workers destroyed industrial machines, which they perceived as a threat to their livelihoods.

But machines were not a threat so much as they were part of a systematic re-evaluation of human labour in relation to machines. Because industrial machines could be operated by unskilled, lower-paid labourers, they threatened to take priority away from highly skilled — and higher paid — craftsmen and artisans. As a consequence, automated labour — and its products — often came to be devalued in comparison to human labour. This was partly because automation meant that similar products could be produced at a lower cost, but the products of automated labour were also seen as lacking the craftsmanship of less automated production processes.

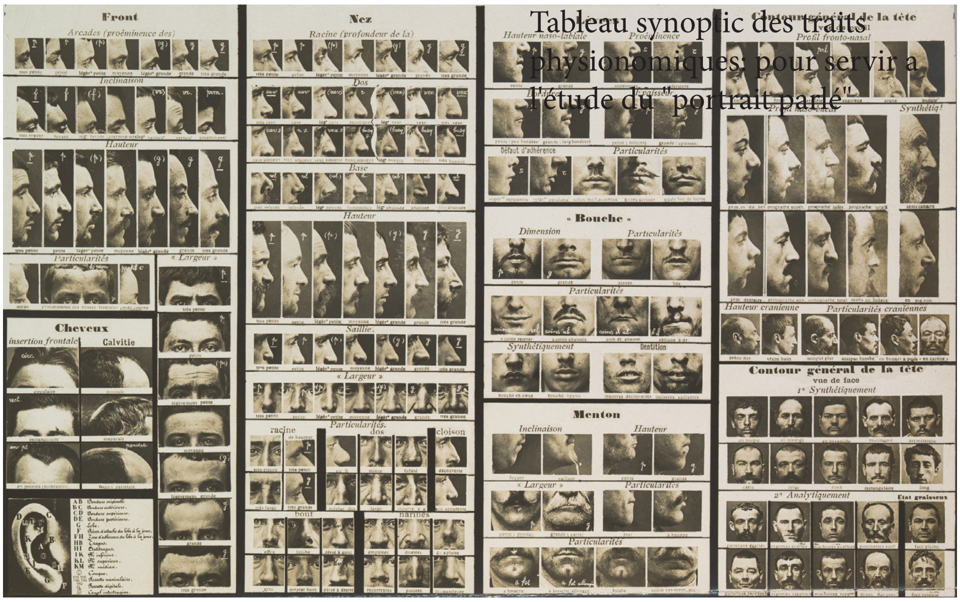



**Fig 49:** Criminal composite photographs. *Tableau synoptic des traits physionomiques: pour servir a l'étude du "portrait parlé"* (Bertillon c. 1909).

A presumed lack of skill and effort entailed in photography, for instance, caused a long-fought struggle for its legitimacy against entrenched ideas regarding painting as a higher form of art. The presumed autonomy of mechanised image production led to the belief that the visual verisimilitude — the appearance of being true or real — of the photographic aesthetic could be taken at face value. Photography indeed proved effective as a form of evidence, such as in crime-scene photography and biometric photographs. Alphonse Bertillon's (c. 1905) standardised system for photographing and of cataloguing images of the human face and its features, called "portrait parlé", or "spoken portraits", derived from the use of the same term for oral descriptions of perpetrators in criminal investigations. The technique — now known as a mugshot — enabled the faces and individual features of criminal suspects to be compared easily against one another. This built on existing techniques of forensic portraiture, collecting anthropometric measurements and highly systematic photographs in addition to qualitative descriptions from witness testimony.

But at the same time that photography proved its potential to reveal the truth, it also quickly demonstrated its potential for illusion. The staging of appearances was zealously grasped from the early days of photography, cinema and pre-cinema (Mannoni 2000). Pre-cinematic devices — precursors to cinema involving related concepts or modalities — often employed optical tricks to achieve movement, illumination, projection and immersive effects. Notable examples of pre-cinematic devices include the magic lantern, zoetrope, panorama, peepshow and stereoscope. These were often shown as public spectacles, in which they were publicised as technical marvels, but also forms of entertainment.

**Fig. 50:** Stereoscopic image of a ghost, for use in stereoscope. (London Stereoscopic Company c. 1856).

Many pre-cinematic devices involve peepholes that place a visual spectacle in front of the viewer's eye or eyes, recalling the construction of the mirror device designed by Brunelleschi (p. 65), which carefully mediated the viewer's point of view. The stereoscope, for instance, requires the viewer to peer through a set of lenses at a pair of images, which are merged by humans' natural binocular vision, giving the person the illusion that they are viewing a single 3D image. The device's placement of the eyes in a particular orientation in relation to the images is crucial to the optical effect, demonstrating directly how visual apparatus may be used to shape perception.

The manipulation of appearances has also been applied towards dubious ends under the guise of scientific accuracy. For example, the appropriation of the mugshot technique by the Nazis sought to prop up discriminatory ideals through the differentiation of kinds of bodies. In phrenology, as well, similar visual cataloguing and differentiation of physiological features was used in order to purportedly "diagnose" those who deviated from a supposed norm. In such cases, attempts were made to identify human intellect, inherent criminality, hysteria, and other qualities merely "by looking alone".[1] (Elkins 1999, 155) In one example given by Elkins (fig. 51), photographs of nostrils are compared, supposedly as an indication of the subject's sensuality.

1: Elkins (1999) describes approaches to the visual differentiation of bodies as "metamorphosis by looking alone", which he argues is "one of the deepest bases of racist and sexist imagery." (155)

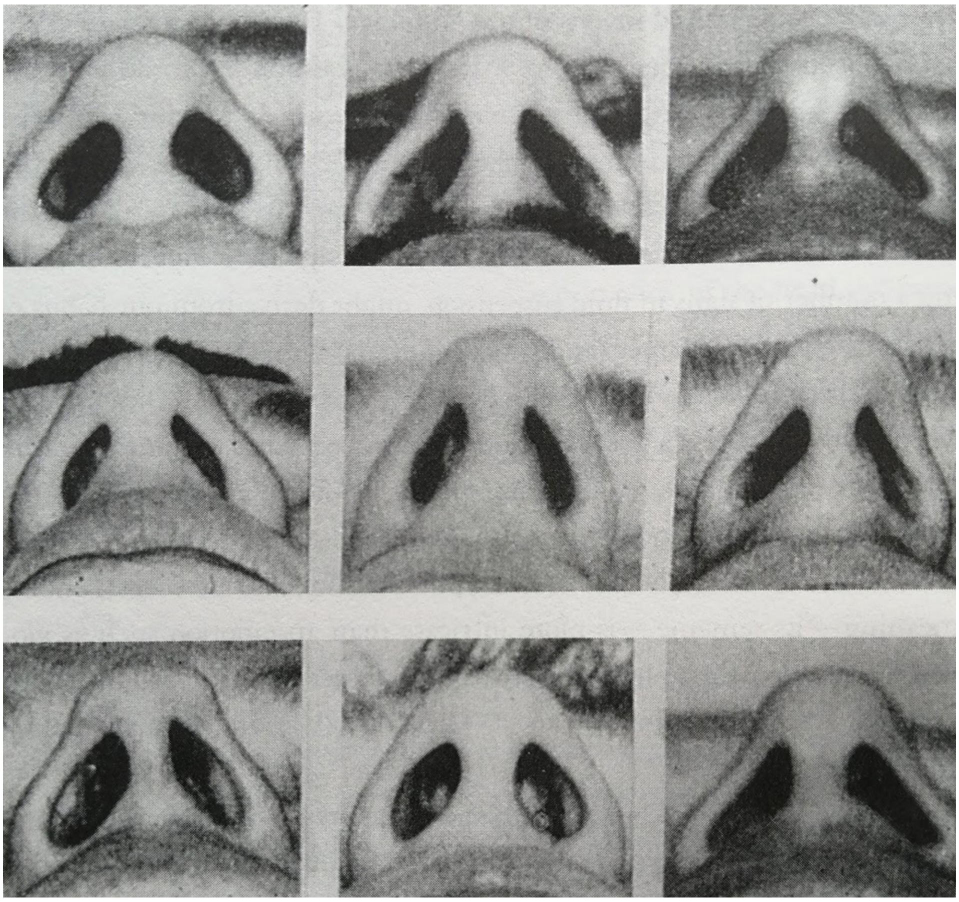


Fig 51: *Nostrils, indicating degrees of sensuality* (Burger-Villingen and Nöthling 1958).

Examples such as these reveal that the assumption of an inherent truth value in images that are subject to technological mediation has serious ramifications. The notion that seeing is believing — especially when technical apparatus is involved — has to do with the turn towards a view of visual artefacts as empirical evidence. This may explain why, in spite of the proven capacity for visual media to be used to create illusions, there is an equally long tradition of tacit confidence in technically produced images. In such cases, science and technology are used to legitimise visual artefacts as presenting a level of inherent truthfulness resultant from the technical methods of their production. For example, the difference between a portrait and a mugshot lies in the rigorous nature of how the latter photograph is obtained, as well as the structures through which it is taken to be visual proof.

Fig. 52: *Cottingley Fairies* (Wright and Griffiths 1917).

Uncritical belief in the scientific nature of visual technologies — combined with the often complex or specialised processes involved — often lends itself to a suspension of judgement when assessing technically produced images. A particularly poignant instance of this involves a set of photographs called the "Cottingley Fairies"(Wright and Griffiths 1917) that were staged by two young girls, using cardboard cutouts to give the appearance that the girls were surrounded by fairies. It is immediately clear to present-day viewers that these are fabricated images, but when the photos were taken, photography was still in its early days. Because of the general public's unfamiliarity with photography, there was initially a degree of contention over whether these images were real or not. This instance demonstrates how changing cultural expectations and technological literacy impact the way in which images are received.

The belief that technologically produced images are closer to the truth than other forms of visual media by virtue of being produced by a machine is not isolated to the past. Like the Cottingley Fairies incident a century ago, ML and artificial intelligence (AI) still provoke a suspension of disbelief, due not only due to popular mythology but also to a lack of sufficient understanding of the limits of the technology. Understanding the processes behind the production of images may thereby be likened to a form of visual and technological literacy, in which one's reading of images may be influenced by taking the technical conditions of an image's production into consideration. But while including the mediating role played by visual technologies as a factor may help to better understand images, discourse has often been polarized into extremes: either delegitimising the products of automated processes, as seen in the devaluation of mechanically produced images or emphasising the autonomy of machines from the humans who design, build, program and operate them.

The involvement of machines in image production gave rise to fears around the "death of the author" (Barthes 1967), which continue to shape discourses on art today. Many apparatuses, including the printing press, the camera and the computer have each come under scrutiny at various points in history for potentially eclipsing the role of the artist. The myth of the "machine as artist" (Broeckmann 2019) has therefore been an enduring theme in technologically centred art, seeking to address concerns of authorship by simplifying it into binary terms. At times it is used to make the case for machine authorship, but it may also take less obvious forms, such as the use of technical systems to play down the role of human decision-making in the production of visualisations.

**Fig 53:** Computer-generated drawing with hand colouring. *AARON* (Cohen 1974).

In early exploration of the idea of machine authorship, Harold Cohen worked on an AI system, which he named *AARON*, from the late 1960s until his death in 2016. *AARON* was designed to produce images, beginning with simple abstract plotter drawings, which grew to be more complex and even figurative over time. Cohen's relationship to *AARON* is said to have become strained when he began to perceive *AARON's* creations as overshadowing his own role as an artist (Reichardt 2018). At that point, Cohen went so far as colouring on top of *AARON's* drawings (see fig. 53) in an apparent effort to prevent his importance from being eclipsed by that of the machine he had designed. Evidence of Cohen's internal struggle for authorship is evident in his alternation between signing images with his own signature, *AARON's* signature or a combination of both.

Fig. 54: *Portrait of Edmond de Belamy* (Obvious 2018).

More than 40 years later, the myth of the machine as artist persists, with the now infamous sale of *Portrait of Edmond de Belamy* by a group named Obvious (2018). The work was widely panned by the art world for its lack of artistic merit, yet it sold at auction for over $400,000. Using a dataset of European paintings as training examples, the resulting image, produced by a generative adversarial network (GAN), appears similar to a smudged oil painting, complete with what appear to be simulated brush strokes. These are an interesting touch, as they transfer the technical qualities of painting into a medium in which they are not necessary.

The work also stirred controversy due to the degree to which it intentionally obscured the human labour behind the supposedly "machine-produced" image. Obvious's images from that series bear a striking resemblance to images produced — and already made public — by Robbie Barrat (2018), then aged 19, from whom Obvious has now acknowledged that they borrowed the code for their project. It is unclear to what extent Obvious did anything that would differentiate their creations from those of Barrat. Additionally, the algorithm for creating this portrait — or rather, a simplified version of it — is inscribed in a handwriting-style font in the bottom right-hand corner of the image, as if to indicate this as the algorithm's signature on its creation.

Currently, international law either prohibits or does not acknowledge copyrights for the creations of machines. According to the World Intellectual Property Organization, "traditionally, the ownership of copyright in computer-generated works was not in question because the program was merely a tool that supported the creative process" (Guadamuz 2017). While the code employed by Obvious was written by Barrat, the images using that code are legally considered equivalent to those created using any other kind of tool. This means that protections for the intellectual property produced by algorithms could become difficult to define, as the use of algorithms to produce visual content – or to even write other algorithms to in turn produce images – becomes more commonplace.

What this means for the use of ML in art contexts is that it is an instance in which assumptions about the relation between art and technology greatly shape the potential of its outcomes. In the same way that technology facilitates new possibilities for image-making, it also has limiting aspects. As with any tool used in art, the technology itself exerts its own parameters on the process. In the case of GANs, this means that not only are many artists using the same kind of ML architecture but also they are often using the same or similar code or image datasets. As a result, many ML-produced images have a great deal of visual resemblance to one another. For example, comparing several GAN images side by side, similar compositional, chromatic, stylistic tendencies become apparent. And the use of common image datasets such as ImageNet also imbues the results with visual particularities that give them a distinct aesthetic that is noticeable in the outcomes of models trained on such datasets.

The debacle around the *Portrait of Edmond de Belamy* (Obvious 2018) is indicative of more than just its dubious claims to machine authorship, as it speaks to the neutralisation of many human design decisions that have not only gone into the ML systems themselves but also their applications. Printed in oil on canvas, placed in a pompous gold frame, displaying a non-virtuosic rendition of European portraiture showing a male sitter, which is then "signed" by an algorithm, the work distils multiple traditional assumptions about value in art into a single image.

### 3.2 Nonhuman Photography

**Fig. 55:** Example of nonhuman photography from the series *Active Perceptual Systems* (Zylinska 2014).

Joanna Zylinska (2017) has referred to highly automated forms of image production, such as CCTV, drone media, medical body scans, satellite imaging, depopulated landscapes and QR codes, as examples of what she calls *nonhuman photography*. These express a displacement of the human from playing anything more than a marginal role as subject, author or viewer. Nonhuman photography, she says, is not principally *of* the human, *by* the human, nor *for* the human (2017, 5).

In this sense, nonhuman photography leads us to an enduring paradox of the posthumanist drive to de-anthropomorphise the human gaze. Attempts to step outside of the human perspective are continually thwarted by the fact that whatever means are used to do so nevertheless impose elements of the human upon that which is viewed. The persistent normalisation of the human point of view that is found in attempts towards a nonhuman photography lead, ultimately, to the conclusion that modes of nonhuman photography are only nonhuman to a certain extent. Like automation, we may understand nonhuman forms of visual processing by degrees, but never in-itself nor as separable from human influence.

Calling highly automated visual technology "nonhuman" is not to say that they do not involve humans at various stages. It is meant to denote visual technologies that are radically indifferent to the human, rather than exclusive of it entirely. This means that a given instance of nonhuman photography may involve human elements, but that the human contribution therein is considered to be inconsequential.

In such a way, the image-making process and its outputs are framed as ambivalent to the viewer. But, we may ask, what is an image without a (human) viewer? What role do images play if we cannot perceive nor interpret them? As such, the nonhuman image defies our very understanding of what an image may be because we have no — or very little — access to it. Considering the production of images without the direct intervention of humans — as subjects, producers or audience — radically shifts our expectations of what images are and do. The indifference of the process, that the image is not beholden to its audience for validation, thereby places the image in a position of sovereignty from the act of viewership.

But although it is aimed away from human subjects in its subject-matter and is orchestrated outside the direct control of humans, it would be hard to say that nonhuman photography ever escapes the influence of human intentionality. Even when visual technologies are automated to the degree that they no longer act directly in the service of human ends, it does not answer the question of who nonhuman photography is for, if not for humans. On the one hand, claims for crediting machines or computational processes with the autonomous creation of images fail to grasp the importance of the creation of the systems that in turn produce an artefact. Yet crediting a human or humans alone would be to leave out the significance of machines and machinic processes in the production of images.

As we understand from looking at various kinds of human-machine cooperation, it is often difficult to draw a line between human agency and the performance of machines. These perspectives are often interlinked, as technological apparatuses have a highly variable degree of influence over processes of image production. This is in opposition to the assumption that automated technologies efface human action from the process. Rather, the automated production of images involves degrees of cooperation and a sharing of agency between humans and machines. Thus, variable levels of agency may be attributed to a device, itself, in human interaction with machines.


Fig. 56: *Phenotypes/Limited Forms* (Linke and Hanappe 2008).

For example, Armin Linke and Peter Hanappe's (2008) *Phenotypes/Limited Forms* presents a mostly autonomous image production system that engages visitors to participate in the production of a personalised picture book. The installation affords user interaction, yet it causes an unusual dynamic between the visitor and the technical system. While the system appears to exist purely to meet the aesthetic desires of humans, it also requires them to act in particular ways in order to make it perform as intended.

Upon entering the space, visitors are invited to select from an archive of 1000 images, grouping a selection of 10 images together for display on specially-designed wall ledges. When satisfied with their curatorial selection, a visitor may place their images in a designated area, from which sensors identify the respective images by means of RFID chips and they are prompted to give a title to their creation. A printer then prints out a unique edition of a book containing the visitor's selected images, and its title is projected on a wall in the exhibition space. The highly automated process in which visitors thus participate overturns the role of the curator by inviting the visitor to make selections from a large archive of possible images that can then be displayed, as well as involving the visitor in the editorial process in the publication of their own book.

What may not be immediately apparent to those who experience this work is the seamlessness and indifference of interactions between humans and machines during the image-making process. The system is so highly automated that it gives the feeling that the visitor is subjugated to the system — entering into *its* space, participating in *its* fulfilment of a task. On the one hand, the machine is put to work for humans, producing images for them. But we may also think of it as the machine merely cooperating with humans, who assist in the performance of its image-making program. Linke and Hanappe place the individual viewer in the curious position of being at once included and excluded from the narrative, possessing at the same time as dispossessed of agency. *Phenotypes/Limited Forms* (Linke and Hanappe 2008) thereby offers an angle into the autonomy of the art-as-system from the artist(s) as well as from the viewer. The work gives the sense that the viewer enters the space of the artwork, in which the system or ecosystem reacts to — but does not necessarily yield to — the human presence.

In this example, not only is it difficult to differentiate the role of the human from that of the machine in image production, but the human-machine relation may also vary in degree at different stages of interaction. Expressions of agency between humans and machines are thereby understood not as fixed dynamics but as being in flux and subject to temporal change. The variable positions of human-machine cooperation that arise at different stages of image production may be thought of in terms of preprocessing, coprocessing, and postprocessing (Aarseth 1997, 135).

*Preprocessing* is exemplified by forms of automation in which a machine or system is set up and run to produce an outcome. Human intervention is necessary at the beginning of the process but is not required after the process has begun. The examples of nonhuman photography given by Zylinska (2017), for instance, primarily involve preprocessing, after which they run by themselves. *Coprocessing* involves a higher degree of interplay and collaboration between the human and machine. This occurs, for instance, in situations where artists respond to the actions of a machine, which in turn influences the creation of a resultant image. Finally, *postprocessing* refers to the processes and curatorial actions applied to media artefacts after those performed by machines have been completed.

These positions in image processing are not mutually exclusive. That is to say that coprocessing, for example, may apply to the cooperation that occurs in other stages, such as preprocessing or postprocessing. They may also refer to the respective roles played by human and machine at different times in a single encounter. Thus, even when a human is not present or is not in direct control of a process, there is still a degree of human participation that may have gone on in the preprocessing phase: in the design, programming and setup of visual technologies. Long-term, unmanned video feeds present such an example in which human intervention is minimised, yet present. Even in the case that such a system might continue to produce images beyond a doomsday scenario in which all humans are wiped out, the system owes its existence to the actions of humans, whether or not they continue to participate in its enactment.

For example, a GAN involves the input of visual data in its initial stages, in the training of a model. This occurs in parallel to non-visual processes that intermittently involve the output of images. GANs also involve levels of human participation that vary at different stages of the process, primarily requiring higher levels of intervention during preprocessing, but also in some cases involving a considerable amount of postprocessing. Although the processing stage is itself performed by a computer, that is also subject to the agency and intentionality of human subjects who orchestrate and oversee it.

Nonhuman agents, such as animals, may also participate in the production of an image, in the case of some of Zylinska's (2017) examples of nonhuman photography. But these scenarios fall victim to the same logical problem discussed previously, that such circumstances are presumably derivative of human intervention, whether directly or in a diluted form. Animals triggering photo snares or even intentionally pushing the shutter release of a camera could, for example, be considered tertiary human-controlled image-making processes in the sense that they may involve nonhuman agency, but nonetheless involve human intentionality in an indirect manner.

In contrast to approaches prioritising the idea of the machine either as merely a tool or as a sole author, some artists have also worked with the idea of sharing agency between themselves and the technologies they work with. This includes explorations of the possibility for a digital tool to play an interpretive, and even creative, role in the production of images. Adrian Ward's *Autoshop* (1999), which could be described as a subversive take on Photoshop, uses AI to react to user behaviour and to vary the visual outcome accordingly. This means that the program thus plays an increased role in deciding how the resulting image will appear in comparison with traditional photo-editing software. Similar ideas have been explored in a number of technical online interactive demos, such as *edges2cats* (Hesse 2017), *GauGAN* (NVIDIA 2019), and *Magic Sketchpad* (Dinculescu 2019). In each of these examples, users' simple drawings are interpreted and elaborated upon by neural networks (NNs).

The recent wave of interest around sharing agency with AI has also included a number of performative or interactive projects. Some of these, such as Holly Herndon's *PROTO* (2019) and Actress's *Young Paint* (2019), continue to mythologise an AI performer with which the artists collaborate with. Mario Klingeman (2018), for example, describes his work *The Butcher's Son* as "a neural network's interpretation of the human form" and an "image [that] has been generated entirely by a machine using a chain of GANs". Yet inherent aspects of the process contradict those statements. In the same artist statement from which the previous quotations derive, Klingeman (2018) goes on to describe the process he employed, saying "I control this process indirectly by training the model on selected data sets, the model's hyperparameters and eventually by making a curatorial choice, by picking among the thousands of variations produced by the models the one that speaks to me most."

While acknowledging his own role in the process, Klingeman attempts to play down the degree of human intervention in producing the final image. Not only has he been involved in the preprocessing, setting up the system, he has also engaged in coprocessing of training the model and its hyperparameters, he also participated in postprocessing by selecting one of the many images that were produced as the final outcome. Andy Lomas (2018) (fig. 13, p. 45) similarly asserts the role of the computer in the production of his *Vase Forms*, while also acknowledging making similarly subjective selections among large amounts of generated content. While unproblematic in itself, this is part of a greater tendency for artists to play down their own role in using ML in their practice.

Anna Ridler's *Drawing with Sound* (2017) relies less on the idea of AI as a character in a narrative about the work, treating it instead as a modality of interaction. *Drawing with Sound* involves the artist wearing a special set of glasses with a built-in camera so that the system modulates sound based on her drawing. A feedback loop is then produced between the artist's interpretation of the sound as a score to perform to and the system's interpretation of that performance. This ultimately influences the visual result in the drawing produced.

Ian Cheng takes a slightly different approach in his work, often creating video installations that exist more as ecosystems for an AI system to inhabit. His work *BOB (Bag of Beliefs)* (2018), for example, is an interactive installation in which users can influence the development of an artificial life form through an app. This approach treats the ML as less of an agent in the artistic process, instead framing the system as an artefact of AI.

Laura Beloff's (2014-2016) *Fly Printer* demonstrates the idea of hybrid intentionality between the artist and nonhuman agents — biological as well as technical. The work takes the form of a small ecosystem in which fruit flies live and are provided pigment-laden food to eat. Over time, the flies' colourful excrement builds up patterns on the base of their enclosure, which are interpreted by a NN. The neural network attempts to assign categories to the arrangements of fruit fly waste, applying a technoscientific approach to a disorderly biological process.

## 3.3 Adversarial Approaches in Art

Approaches which disrupt the usual application of science and technology, such as in adversarial approaches, are particularly relevant for the way that they demonstrate differences in the interpretive processes performed by humans and machines. Designed to be interpreted — or rather, misinterpreted — by machines, fooling images have been a source of inspiration for many artists. In a capacity similar to the optical tricks of pre-cinema, adversarial images often instrumentalise the fact that they are capable of being read in more than one way. As such, adversarial images help to visualise the differences between biological vision and the visual processes performed by machines. Producing an image with the express intention of fooling a computer uses differences between the way in which humans and machines process visual information in an effort to probe the robustness of an ML system.

Such adversarial images have no obligation to look like what they are because effectively, they are what they do — the operation that they perform, which in this case is to appear as one thing to human subjects while being read as something else by an ML system. Therefore, an object that has been designed to look like a turtle to humans and that is classified as a rifle by a computer (Athalye et al. 2017) is successful or valuable to the degree it performs its task.

> You are a set of coordinates — the unique contours of your very own face — their virtual cipher. (Malick 2019)

Many artists have sought to appropriate and to break the typical power dynamics ML engages in by responding to the increasingly widespread use of biometric surveillance that employs facial recognition, with designs and techniques for evading this control. Unsurprisingly, the face has been the subject of numerous artworks, many of which involve elaborate strategies to regain one's privacy and camouflage oneself from surveillance cameras.

In this sense, the face has become a battlefield, with various interests seeking to capture or to obscure it.

**Fig. 57:** Example of counter-CV styling. *CV Dazzle* (Harvey 2011—2017).

A well-known artistic example of an adversarial approach to surveillance is a look-book of suggested styling tips for evading face detection, entitled *CV*[2] *Dazzle* (Harvey 2011–2017). The strategy employed involves make-up and hairstyles that break up the features of the face in order to thwart facial recognition. The makeup and hairstyles presented in the project decorate models' faces with colourful, angular lines, patterns and tufts of hair in unexpected places. By disrupting the symbols that constitute a face for computer vision, these styles render the wearer's face undetectable to facial recognition systems.

Other approaches to camouflaging the face include Harvey's (2016) *Hyperface*, which consists of a fabric printed with a pattern that is read by CV as numerous faces. This allows the wearer to disguise their face by hiding it within a sea of other faces. Aram Bartholl and Kyle McDonald's (2012) *How To Avoid Facial Recognition or YOU GOTTA FIGHT FOR YOUR RIGHT TO PAAARTY (ANONYMOUSLY!!)* suggests a simple hack. By simply tilting one's head to the side, one could ward off facial recognition — at least with the level of facial recognition software commonly used at that time.

Zach Blas (2011–2014) has created several projects concerned with facial biometric data and surveillance, including *Facial Weaponisation Suite*. In the various iterations of the project, he used the aggregated facial data of groups of people, which were then turned into physical masks worn by participants in performances. For example, the facial data of people who iden-

2: Computer vision (CV)

tified as homosexual was made into composite 3D-printed “fag face masks” (2012). The idea behind this approach is that by creating a representation mixing the biometric information of different people together, the masks make the wearers untraceable to biometric surveillance technology. Sterling Crispin’s (2015) *Data-Masks* were created by reverse engineering facial recognition and detection algorithms to produce a 3D-printed representation of a face. The bulging surfaces of these masks resemble some of the masks from Blas’s *Facial Weaponisation Suite* and employ a similar approach by turning biometric facial data into 3D forms.

Hito Steyerl’s work related to this topic, *How Not to be Seen – A Fucking Didactic MOV File* (2013), looks at the dependence of technologically mediated visibility on registration. It also proposes different approaches for not being seen by computers, including, for instance, becoming the size of a pixel (Steyerl 2013). By conflicting with the registration of a visual technology, we may conclude, one becomes unreadable to it. The piece prominently features a military aerial registration mark, used to calibrate cameras in aeroplanes, among several other registration technologies such as green screens. Visibility, Steyerl asserts, is tied as much to ones overt relationship with systems of visibility in the sense of surveillance technologies as it is with one’s *social* visibility and status within a society. This work introduces registration as a necessity for the legibility of algorithmic images.

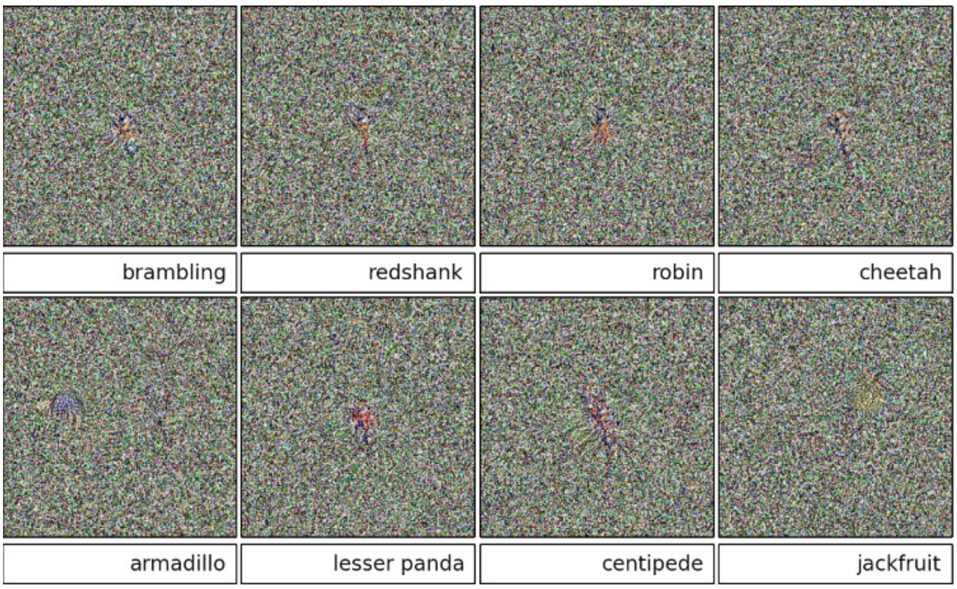



**Fig. 58:** Adversarial images produced using direct encoding. *DNNs are Easily Fooled* (Nguyen, Yosinski, and Clune 2015).

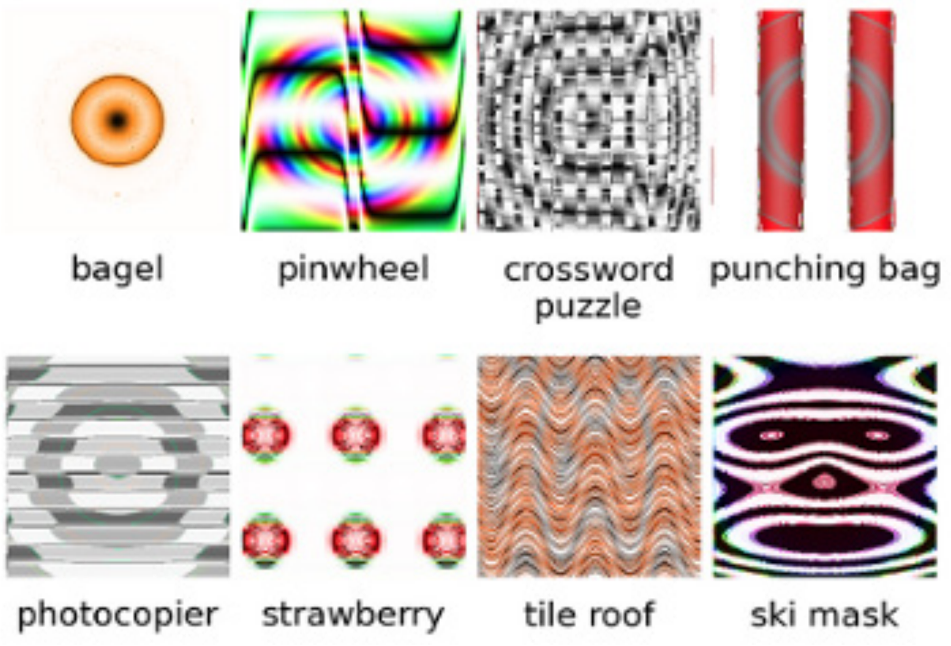



Fig. 59: Adversarial images produced using indirect encoding. *DNNs are Easily Fooled* (Nguyen, Yosinski, and Clune 2015).

Various kinds of adversarial image examples exhibit different degrees of visual perturbation, referring to the human-visible impact of modifying images for an adversarial attack. At one end of the spectrum are images that modify the human-interpretable image as little as possible, such as the one-pixel attack (Su, Vargas and Kouichi 2017). At the other end lie images that are modified to the extent that they do not resemble anything for human viewers, such as the noisy images produced in the *DNNs are Easily Fooled* (Nguyen, Yosinski and Clune 2015) paper (fig. 58). It is notable that in the indirectly encoded images from the same paper (fig. 9), some of the images bear a strong visual resemblance to their target class, in spite of being generated to be visually abstract.

### 3.4 Identifying Abstract Art

Though the examples in the *DNNs are Easily Fooled* (Nguyen, Yosinski and Clune 2015) paper have been gathered together by the authors for the purpose of proving how easily fooled deep neural networks (DNNs) are, these images instead give the impression that DNNs are curiously skilled at interpreting abstractions of a wide class of objects. Noting the degree to which DNNs were able to accurately label abstracted images for a wide range of different image classes, I conducted explorations looking at how abstraction is addressed in image classification algorithms.

The experiment focused on the fact that non-representational images can be a great challenge for algorithms to classify. In order to test this idea, I compiled a data set of digital images of abstract paintings. This was done by collecting the first 100 results for 'abstract' in the Metropolitan Museum of Art's online database, based on the museum's own system of tagging items. Each of the images was then subjected to analysis using the Wolfram image identifier (Wolfram 2015), a successful online image classification system. The reason for using this particular program is that it is a tool that makes ML accessible to the general public.

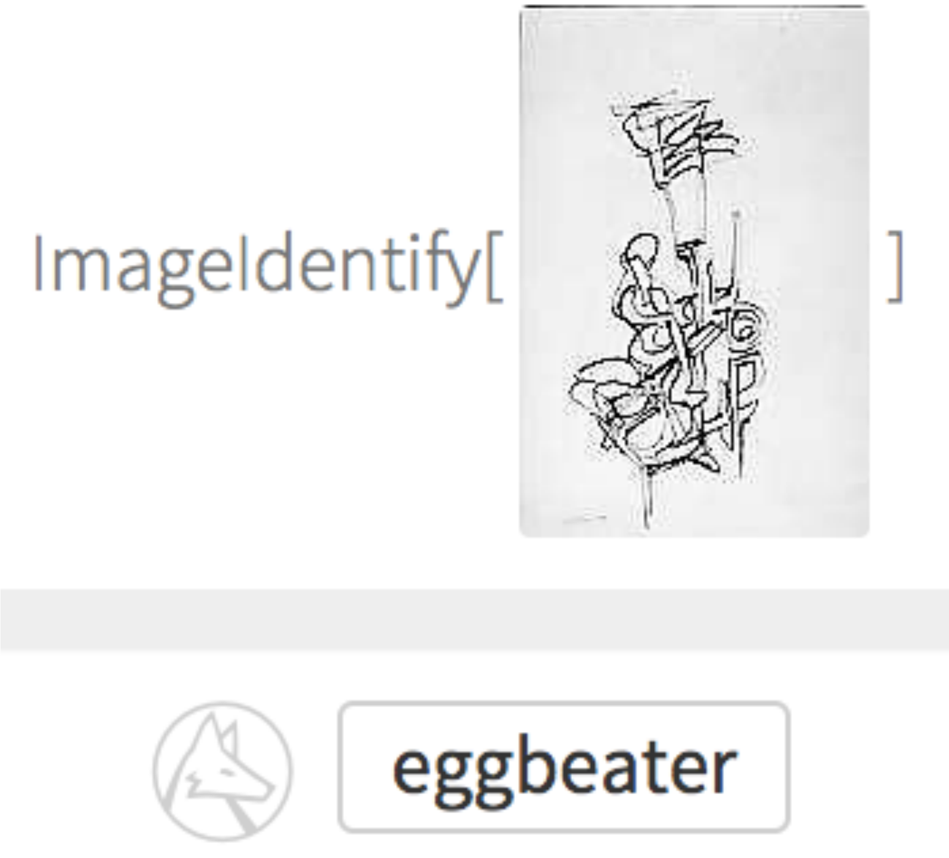



Fig. 60: Documentation from experiment with Wolfram Image Identifier. *Identifying Abstract Art* (Lee 2018).

The results of the experiment showed that the program was unsuccessful in identifying abstract paintings. A total of 98% of the abstract images were categorised incorrectly as a wide variety of different classes of objects. Only 2% of the images were correctly categorised as paintings, which may be attributable to the fact that the images that were successfully classified included frames. The experiment provided a few insights into the relationship between abstraction and representation in algorithmic image systems concerning the levels of meaning and interpretation that are involved in viewing images, which are not the same for humans and machines. Rather than framing the miscategorisations that occurred as failures, as they are on a technological level, their ambiguities can lead to new ways of understanding the cooperation between human and machine visual interpretation.

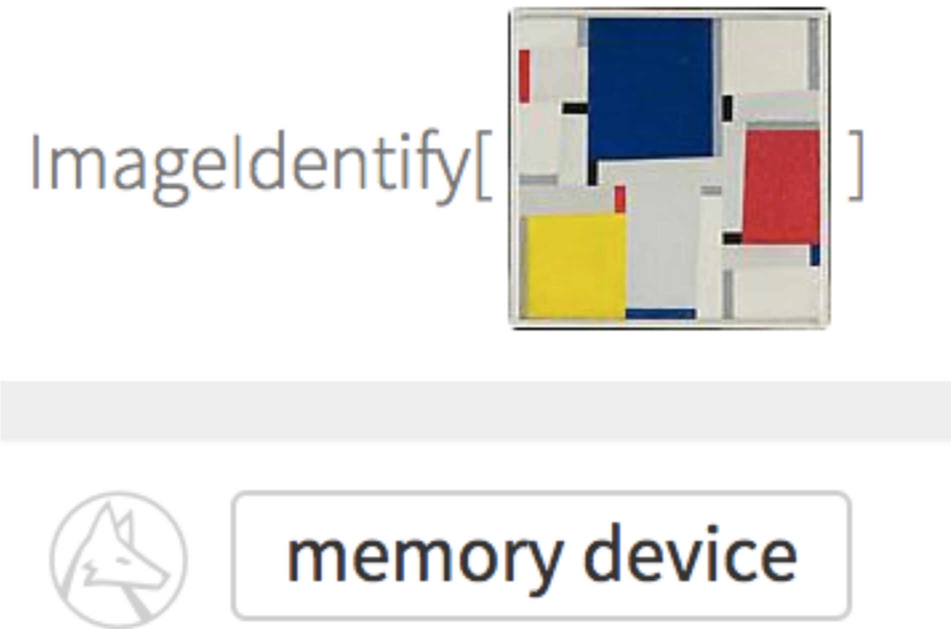



**Fig. 61:** Documentation from experiment with Wolfram Image Identifier. *Identifying Abstract Art* (Lee 2018).

Although the abstract paintings analysed in this experiment bore little or no visual resemblance to the classes assigned to them by the computer, each misclassification could be interpreted as adding layers of poetic meaning to the respective image. For example, a hazy black and white image labelled as "atmospheric phenomenon", and a composition of dabbling brush strokes labelled "imaginary being" take on different connotations when associated with those words. The label "memory device" applied to a painting by Piet Mondrian, too, suggests conceptual connotations that viewers may not necessarily connect to this image based on looking alone, but which nonetheless add to the experience of the work.

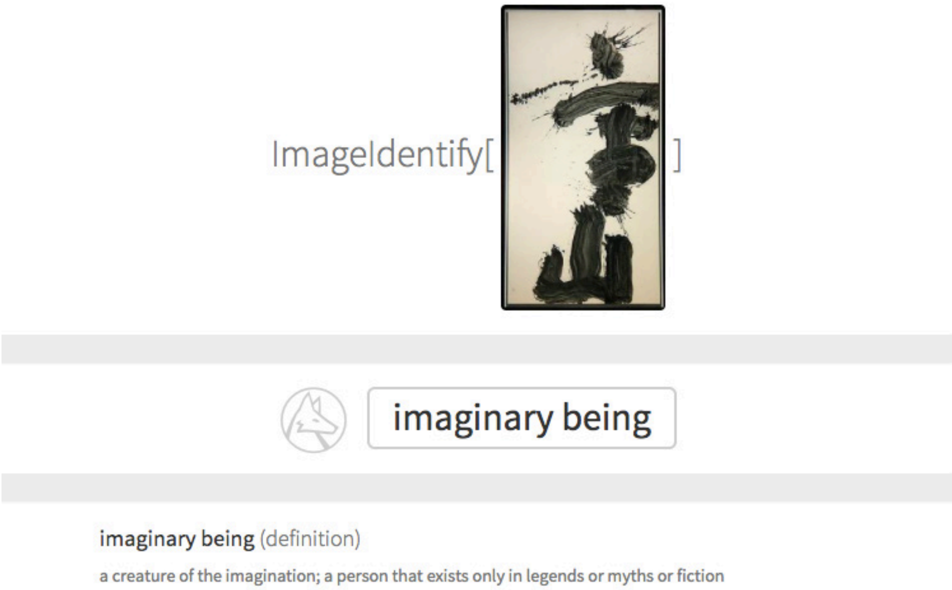



**Fig. 62:** Documentation from experiment with Wolfram Image Identifier. *Identifying Abstract Art* (Lee 2018).

Abstract images are not designed to function as adversarial examples, but the results of this experiment suggest that they are nevertheless successful at fooling otherwise successful classification algorithms. Achieving a 98% misclassification rate is close to that of expressly designed adversarial examples. This may be due to a tendency of classification algorithms to assume that there are image classes for each kind of input image. Therefore, the results of the experiment suggest that adversarial images may owe their success not to being specially designed to trick algorithms, but rather to being abstractions for which there is no image class in a system that insists that all images belong in a category.

The ability of an ML system to pick up a semantic cue, like the picture frames in *Identifying Abstract Art* (Lee 2018), demonstrates an interesting capacity to associate patterns with meanings. This is much the same as any use of language, but if we move beyond the anthropomorphising tendencies that often prevent deeper discourse on this subject, this is an interesting development related to conceptual art. Pattern, and not just in the visual sense but also in the sense of frequency or other associations, may be associated with virtually any system of types or categories. Therefore, the detection of the pattern that “picture frames — whatever they are surrounding — mean painting”, while straightforward, offers an interesting insight into the structures that may be overlooked as externalities, but that greatly influence a given interpretive system.

Recalling the epigraph by Vilém Flusser (1983) from the beginning of this chapter (p. 74), the examples covered here share an emphasis on how technical processes colour our view of images. The common belief in the autonomy of visual processing tasks which are performed by machines offers a better understanding of lingering ideas which inform discourses on current ML applications. While it is generally understood that machines, ML and AI are created by humans, there is nonetheless a recurring desire to think of them as separate from human intervention. This is responsible at times for attempts at measuring the legitimacy of artistic works by the degree to which they have been mediated through technoscientific processes.

Technically produced images are no less subject to error and manipulation than those that are produced manually, but the association with technical and scientific processes is often used to legitimise visual media. The implementation of technical processes in the production of images does not necessarily lend them an inherent truth value. Instead of a reflection of a neutral view of the world from the perspective of a machine, technically produced images should rather be viewed as representations of the interpretive and mediating processes applied to certain source material. The next chapter examines this phenomenon from the angle of the technological mediation of perception and the production of images.

## 4. Images, Machines and the Limits of Perception

> But the human eye perhaps finds itself in a moment of misapprehension. The machine constructs the image and we construct another image out of what we think we are seeing. (Pohflepp 2017)

Algorithmic forms of media often entail the influence of processes that may or may not be visible to humans, while enabling visual processing tasks to be performed by machines, making it possible for there to be a substantial divide between the computational and visual attributes of an image. Various theories covered thus far in this thesis have addressed aspects of this, including the algorithmic and procedural qualities of the softimage (Hoelzl and Marie 2015), contrasting between optical and non-optical media (Kittler 1999, 225), the interfacing that occurs between an image's surface and its subface (Nake 2008) and nonhuman photography (Zylinska 2017).

As we understand from the previous chapter, the emphasis placed on algorithmic procedures and on automation in theories on current visual media often problematise the role of machines in relation to that of humans. The complex interplay between visual and non-visual processes, and between human and machine expressions of agency, is commonly understood either through cybernetic metaphors or by way of dichotomies that oversimplify what is at stake therein. Cybernetic comparisons facilitate an understanding of the similarities and differences between diverse systems, but they may also contribute to misunderstandings. Attempts at distinguishing the role of human from machine forms of agency have often led to thinking of these in terms of binary oppositions that do not capture the levels of nuance therein. Through the lens of Harun Farocki's (2004) "operative image" (17) and Jakob von Üexküll's (1934) Umwelt, we examine how machines mediate visual perception and agency.

### 4.1 Operative Image

Harun Farocki's (2004) operative image has been a highly influential theory in redefining what images are, how they behave and how they relate to human perception and ability. Operative — or operational — images are "images that do not represent an object, but rather are part of an operation" (Farocki 2004, 17). This conception of the image as processual in nature, and "not primarily visual" (Farocki), facilitates a ground-breaking reimagination of the image in relation to machine vision (MV).

Farocki's trio of video installations, Eye/Machine I—III (2001–2003) demonstrates what is meant by the term "operative images". Scenes feature a robot performing tasks autonomously, cutting between shots of the robot moving around in a room and shots taken from the robot's point of view, highlighting written numbers in various colours, as if to indicate the robot is "reading" those as salient features. Other video clips show what appears to be a navigational assistance system overlaid with markings indicating what appears to be the system's assessment of features in its environment. Colourful, crudely drawn, pixelated marks on the video designate the edges of a road and various obstructions in the path of a vehicle, as interpreted by MV. Footage taken by drones navigating autonomously in search of targets is alternated with those of a human operator tasked with watching the footage and overseeing remote missile strikes.

The automatic performance of visual processing tasks by computers, robots and drones in Eye / Machine I—III (Farocki 2001–2003) highlights the contrast between human and machine vision, and it underscores the estrangement of the mediated point of view from its typical positioning in place of the human eye into the performance of visual — or rather, spatial — operations. In these clips, one sees that the machine is at times more an interpreter of visual information than a producer of images. The machines in these videos are unconcerned with their visual output and its eventual viewing by humans, indifferently following the procedures they are programmed to execute.

In his well-known text, Phantom Images (2004), Farocki reflects upon the video works of Eye / Machine I-III (2001–2003) and examines how autonomous systems for visual interpretation act as analogues for human vision. Drawing inspiration from "phantom shots" in cinema, "film recordings taken from a position that a human cannot normally occupy" (13), Farocki (2004) examines how technical capacities have enabled cameras to visualise phenomena in a way that had previously been impossible. Citing situations such as attaching cameras to bombs dropped out of warplanes, on the underside of trains or simulating the flight of bullet through the air, Farocki describes the capacity of visual technology to offer the point of view a degree of autonomy from biological vision, often tinged with the threat of death.

Lev Manovich (2001) recounts a related example of the physical distancing of photography from the standard human point of view, in which the attachment of a photographic plate to a hot air balloon enabled the invention of aerial photography[1] (98). The technology was quickly co-opted for military surveillance, a connection paralleled in Farocki's overt focus on how in the context of the Gulf War, technologies such as unmanned drones, robots and remotely monitored machine vision systems brought the automation of visual processes to unprecedented levels. Virilio (1994) refers to the automation of perception through cameras controlled by computers in terms of a "sightless vision" and ultimately a "splitting of viewpoint, the sharing of perception of the environment between the animate (the living subject) and the inanimate (the object, the seeing machine)." (59)

In such cases, the camera takes the human point of view to situations where it is otherwise unable to go, adding alternative perspectives to what may be seen and how. It is not only the physical distancing of the point of view from that of the human position but also the difference in modality that occurs as a result, which is central to Farocki's reformulation of the image. The operative image emphasises that in the autonomous processing of visual information by machines, the visual may be subjugated to the performance of spatial operations. Treating the production of operative images as independent of human vision, the "image", as such, may be played out in the spatial navigation of a robot in a room, without a human-visible output. Such an exercise involves ML in the interpretation of visual information, which enables the operation — that is, the operative image — to be performed.

The plane of human vision is thus exchanged for the performance of spatial tasks such as navigation or object detection and the operative aspect of images takes on more than one meaning. The operative image may result from the performance of operations, or it may be defined by its capacity to operate upon the world, as in the sense of "operative language" described by Roland Barthes (1957, 146), from which Farocki drew the term "operative image"(17). Explicitly examining sensory automation, Barthes points out how visual technologies function as part of the war apparatus, embodying a political agenda with his idea of the "image-at-one's-disposal",[2] (146) which also contributed to Farocki's coining of the term operative image.

In a passage invoked by Farocki (2004) to describe the programmatic use of images, Barthes (1957) describes the potential for images and words to function in an instrumental capacity:

> "I 'speak the tree', I do not speak about it. This means that my language is operative, transitively linked to its object; between the

1: Invented by Félix Tournachon Nadar in 1858.
2: This concept was an initial inspiration behind Farocki's operative image.

> tree and myself, there is nothing but my labour, that is to say, an action." (146)

Rather than representing something other than itself, we recall that the operative image is connected to the real through the enactment of a spatial procedure. Through this connection to Barthes, another dimension is added, in which we see that images are also implemented to act in a particular, communicative, way. As we understand from Vilém Flusser (1983, 26), describes technical images as performing a program in the form of an image, which is orchestrated by technical apparatus. The operator of the machine thus participates in a program performed by the camera to produce an image, which in turn acts upon the world or its audience.

The human operators overseeing the performance of drones, which are shown in *Eye / Machine I-III* (Farocki 2001–2003), take on a passive role, mostly watching but also having the possibility to push a button to fire a missile. This cooperation between human and machine incorporates human vision only to the extent that it is necessary to perform the tasks at hand. The video clips comprising the artwork are taken from one context and placed in an art context in order to make certain aspects visible. In this sense, images are not only programmed but also program their viewers, as they are explicitly designed to be received in a particular manner.

For Farocki, the autonomy of machines gives rise to operative images, which do not need to be visualised, and that are orchestrated as manoeuvres, or spatial operations. This is a radical form of autonomy, of the machine from the agency of humans, but also of the image from human visual perception. Farocki's operative image thereby subjugates the image to the performance of technology. The image, for Farocki, is merely the side-effect of the operation, not the overt end goal of the operation. Kittler describes this as a paradigm shift from optical media (1999) to the prioritisation of computation (225). As we recall, optical media such as photography embed optical relations in the surface of the image. In contrast, what is visualised in non-optical media is the product of computational processes.

There is a degree of ambiguity between these designations, as, for example, in the use of optical techniques described previously. Such methods employ both optical and non-optical processes, often using mathematics to systematically simulate optical effects. This is also the case in digital images, which may be based in computation, but nonetheless adhere to the constraints of human optical perception. A digital photograph is a reflection of optical relations that have been captured by a digital camera. The image itself, in digital format, may not be inherently subject to the constraints of optical principles, yet it is nonetheless the product of finely tuned optical technology.

While images produced using ML may not necessarily engage optics in a direct sense, they still bear its influence indirectly, even if only in its output. This is apparent in the compatibility between some ML-produced images and human vision, for example, which do not appear to us as photographic images by accident, but because they have been designed to be that way. As a result of embedded optical relationships in the surface of the image, the optical nature of an image persists beyond the algorithmic turn toward non-optical media because optics is a assumed as a prerequisite, whether or not it is directly implemented.

“Computer images are more than visualisations of a computation, and they are more than computations of an image.” says Frieder Nake (2008, 105). He refers to the processes that lie, metaphorically speaking, “behind” the visible surface of an image as its *subface*. The visible surface of an image displayed on a screen, for instance, involves computational processes that are interpreted into an intelligible visual form. The image does not exist merely as a surface, coupled together with its subface, but also includes the mediation or interfacing that occurs between these parts — or rather, states — of the image.

It may also be argued that such a dichotomy exists between the surface and the subface of all images in which the process for producing an image is not considered identical to or reducible to its visible attributes. Regardless of the mode of production employed, even very simple, analogue techniques such as drawing involve processes that are not included as a visible element of the image. The pencil or ink brush drawn across paper by a human hand could be viewed as the subface of a drawing, in spite of the fact that it occurs physically in front of its surface.

The operative image can be seen as a departure from such dichotomies between visual and non-visual, or optical and non-optical, media, in which the image *is* the operation, not its product. In the context of ML-produced images, this can also be understood to be the case in adversarial images, which are demonstratively technical. That is to say that, while ML-generated images may or may not bear visual evidence of their production process, they frequently rely on a degree of technical literacy in order to grasp their meaning.

Therefore, regardless of whether or not the production process of an image is perceptually accessible to viewers, the role played by technical apparatus and processes in image-making contributes significantly to the way in which they are framed, from a cultural and theoretical standpoint. This is especially noticeable in the commonplace differentiation between images that may be similar in appearance but entail radically different technical processes in their execution. As such, we understand the algorithmic qualities of images to be tied to the execution of spatial — and not necessarily visual — operations.

## 4.2 Umwelt

> But in fact, map and territory, world and database, engender each other in what we would call, drawing on Jacques Lacan, a speculative feedback loop. …
>
> If the world exists, that is, if the world exists in our experience, it is not as a datum, but as a heterogeneous ensemble of both physical and digital data. (Hoelzl and Marie 2015, 98)

There is a paradoxical interconnection and at times incompatibility between human biological vision and imaging processes performed by machines. Though attempts at distinguishing between the visual and nonvisual attributes of images, and between human and nonhuman authorship, these are nevertheless a recurring theme in discourses surrounding the technical nature of images. Understanding images instead in terms of the mediating role played by visual technology offers a vital perspective on the dynamic qualities of images.

Technology has the capacity not only to act as an extension of human ability and perceptual experience, as examined by Maurice Merleau-Ponty (1945) and Martin McLuhan (1964), but also to impact the way those are interpreted. Postphenomenology holds that technology plays a hermeneutic (Ihde 2009, 43) role in augmenting but also altering that experience. Far from faithfully representing reality in an impartial manner, as has been suggested regarding photographic and other forms of technical media, producing images intercedes in the mediation of experience. Technological implements may thereby extend our abilities to see in ways we have not seen before, but the act of translation between forms causes a qualitative altering of the perceptual phenomena involved.

The technological mediation of human perception thereby results in a feedback loop between how humans perceive the world and the visual media we in turn produce. In this sense, the image is less a reflection of an artist's representation of the world as the artist's perception of the world as mediated through scientific instruments. In so doing, the viewer's gaze is positioned in the perspective of the author, machine, and processes involved. To think about this in terms of image-making, the modulation of the perceivable through technology, as described by Merleau-Ponty (1945) and McLuhan (1964), may tangibly affect the images that are in turn produced. For example, devices that enable us to see in new ways, or to produce new visual effects, also alter the role played by the resulting visual media. In the same way that visual technologies play a hermeneutic role in mediating perception (Ihde 1990), images, too, may take on a mediating capacity between viewers and objects in the world.

Our ability to build technologies that then in turn mediate relations with the world (Heidegger 1977) is understood as positional and limited by our place as subjects in that relation. According to María Antonia González Valerio (2018), such technological mediation of reality not only shapes our ability to interact with the world but actually plays a deeper role in our construction and understanding of reality. This means that not only may we build tools, which in turn allow us to shape the world around us, but this also has a reverberating effect on our relation to the world we construct.

Verbeek (2005) asserts that agency is not exclusive to the human, and that "mediation always involves several actants that jointly perform an action" (156). According to this perspective, a tool may assert its own level of intentionality on the process in which it is used. Such instances of *cyborg, hybrid* or *compound* intentionality, to use Verbeek's (2008) terms, address various kinds of interrelation between human and machine intentionality as a matter of degrees. Though Verbeek's classifications open up several different ways for shared intentionality to occur, they attempt to split hairs in such a way that these terms are rendered rather clumsy to put into practice. Nevertheless, they offer alternatives to sharp distinctions between human and machine forms of vision and image-making, instead considering these as intermingled, even indissociable.

This is not to say that human vision and machine vision (MV) are completely compatible. As we understand from the examples in the previous chapter, adversarial approaches have the capacity to highlight instances in which human and machine visual processing are misaligned. The use of such methods in artistic practice is revealing of longstanding tendencies to draw comparisons between human and machine forms of vision, as well as between the image production processes employed. At the same time that such cases make apparent the differences between the various perceptual systems employed, they also underscore the difficulty in making hard and fast distinctions between human or machine vision or ability.

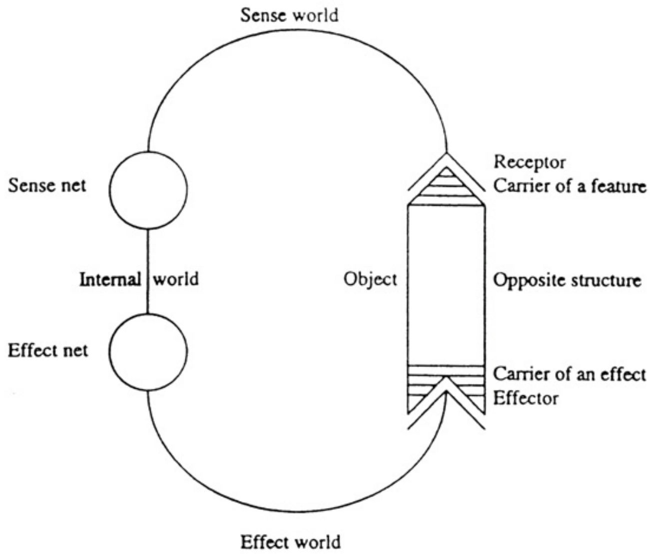



Fig. 63: Illustration Based on *Early Scheme for a Circular Feedback Circle* (von Üexküll 1920).

The concept of Umwelt (von Üexküll 1934) from sensory ecology offers insight into the mediating role played by machine learning (ML), and its entanglement between visual and non-visual, human and nonhuman. The term *Umwelt* refers to an organism's sensory perception and its contingent ability to react to its surroundings. That is to say that an organism's ability to perceive directly conditions its engagement with its environment. Though it specifically addresses biological organisms, the notion of Umwelt also gives us a particular gateway to understanding nonhuman processes of sensory perception. It also enables an understanding of how one's experiential environment may be mediated through the use of technology.

Von Uexküll pioneered thinking about the sensory abilities and agency of nonhumans, such as the sensory world of the humble tick (1934). The relatively limited sensory abilities of the tick make it a useful subject for the study of sensory perception. Within von Uexküll's framework, the perceivable world of an organism is bound in a circular relation between its organs of perception and its ability to act upon the sensory information it takes in. As such, the Umwelt has a two-fold nature, defined by an organism's perceptual apparatus and by its situation as an agent within its environment. For example, in the absence of its perceptual signifiers, the tick ceases to exhibit behaviour linked to respective stimulus. Demarcating the limits of the tick's perceptual apparatus in such a way enables the establishment of a clear link between sense and agency.

Older reCAPTCHA (von Ahn et al. 2008) images composed of distorted text, for example, reveal an intimate knowledge of the differences between human and computer vision, which has been implemented in order to make images that are human-readable but difficult to read for computers. In this sense, the image is framed as a computational problem to be solved, more so than a visual representation of the world. This is the case, for example, in reCAPTCHA images, which, intended as a Turing test, pit human ability against that of "current computers" (von Ahn et al. 2008). With this phrasing, the creators of reCAPTCHA emphasise the fact that computer ability is continually changing. This contributes to a need for the continual adaptation of systems like reCAPTCHA against an onslaught of attempts to beat them.

While it accounts for the variability of the ability of machines to perform various tasks, the one-size-fits-all approach of reCAPTCHA is also undermined by the fact that human ability is also highly variable. At the point at which a computer outstrips human ability at interpreting images, the system of measurement no longer functions, because the inability to perform the task is the sole criteria of distinguishing human from machine. For this reason, reCAPTCHA has largely gone invisible, analysing other data in the background instead of requiring users to assert their humanity.

*One of Them is a Human* by Maija Tammi (2017) is a good example of the uncanniness of attempting to distinguish the human from the nonhuman and the real from the hyperreal. In the exhibition, the artist exhibits one portrait of a human sitter among several portraits of hyperrealistic androids, challenging viewers to identify which is which. In so doing, the work also points out the level of difficulty that exists in differentiating between human qualities and those ascribed to robots or to inanimate objects.

Traditions of labelling image-production technologies as entailing more or less visual properties or more or less human intervention distract from the fact that images involve both visual and non-visual properties as well as being the product of technologically mediated action on the part of humans. Not only does this falsely assert that the distinctions between such categories are more distinct than they are in reality, but it fails to grasp the importance of why such a lack of distinction exists. The technological mediation of perception that occurs in ML images concerns not only the perceptual itself but also the position of technological apparatus within that mediation. Technological mediation of the image causes a rift between the processes that are visible on its surface and those that are not. That said, in many of the examples covered here, the role played by ML is interpretive, determining actions based on analysis of visual data.

Machines may perform visual tasks in a semi-autonomous capacity, yet they are inseparable from the influence of human perception and agency. The interplay between human and machine forms of visual processes places emphasis on the mediation of biological perception, as well as drawing attention to the fact that such mediation qualitatively alters experience in the process. Metaphorical comparisons between human and machine forms of vision have led to the tendency to consider visual technologies as extensions of or even stand-ins for the eye. Yet in spite of the fact that machines may expand the realm of human perceptual ability and experience, there remains a noticeable gulf between our ways of seeing (Berger 1973) and ways of machine seeing (Cox 2016). Machine forms of vision may take the eye to new places, but they also impose their own — machinic — logic onto the process.

Relations between human visual perception and the visual technologies used to augment it hold particular fascination for theorists and artists alike. There are many examples of ML projects explicitly claiming, whether comically or seriously, to teach machines to see. Amy Alexander's *What the Robot Saw* (2019) has an artificial intelligence (AI) create captions for YouTube clips as they play. To a human viewer, this entails either a poetic redundancy by captioning the obvious or by comically erring in ways that reveal it is a computer — not a human — performing the task of applying these labels. Memo Akten's (2017) *Learning to See* has a deep neural network (DNN) make associations between analysed video and visual information it has encountered previously.

Trevor Paglen's (2017) exhibition *A Study of Invisible Images* presents works that peek into the processes at work in ML systems. In his related essay, *Invisible Images (Your Images are Looking at You)* (2016), Paglen argues that the human eye is being rendered obsolete by the machine vision systems, which are displacing it. *Invisible images*, similar to the operative image of Farocki, are made by and for machines (Paglen 2014), with no necessity to be intelligible to a human audience. For example, the installation *Machine-Readible Hito* (Paglen 2017) features hundreds of images of the artist Hito Steyerl contorting her face into various expressions, along with readouts of how each grimace or smile was then classified by a computer according to four categories of emotions: neutral, surprise, sadness, and fear.

Works in this vein often impose a teacher-pupil power dynamic recalling the "I forced a bot to watch 1000 hours" meme, in which internet users post texts purporting to be written by AIs. The comedy lies in a human pantomime of computers performing — or failing to perform — behaviour considered to be human-specific, or in the case of *Machine-Readable Hito* (Paglen 2017), quantifying qualities, such as emotions, which humans take to be unquantifiable. Such works reveal a similar drive to defend the territory of the human from encroachment by machines.

**Fig. 64:** Installation view of *UUmwelt*. (Huyghe 2018).

Referencing the theory of Umwelt in its title, Pierre Huyghe's (2018) *UUmwelt* focuses on the idea of conveying mental images through a complex process of mediation, in which ML assists in the interpretation of a person's neural activity into a visualisation. Presented on large-scale LED-screens within dimly-lit gallery space, the images in the work flicker and morph between unplaceable forms, without ever becoming overtly recognisable as anything in particular. To produce each image in the work, the artist began by communicating the idea of a particular object to an individual through speech alone. Next, the subject was asked to think of their respective object, functional magnetic resonance imaging (fMRI) was used to record their brain activity. The fMRI data was then interpreted by a generative adversarial network (GAN), producing several iterations (see pp. 42–43). The resulting images are animated on video screens, using sensors to modify their appearance based on the presence or absence of viewers in the exhibition space.

Fig. 65: Detail of *UUmwelt*. (Huyghe 2018).

Several elements suggestive of nonhuman perception and agency are included in the installation. It includes a technical system of sensors, which make the work reactive to the atmospheric conditions of rooms, and a population of black flies, which lives in the gallery space throughout the duration of the exhibition. The presence of the insects, often clustered together on the surface of an illuminated screen or other light-source, lends the work an eerie feeling, a feeling that one may never truly be alone in the space.

An interesting takeaway from this piece is that the process of transcoding an image from one medium to another is not one-to-one, entailing a form of translation. This is perhaps most notable in the processing that occurs in translating fMRI data into GANs. There is firstly a significant amount of interpretation in preprocessing the signal into a form that can then be used to generate images using a GAN.

In the way that it ties together conceptualism with the visualisation of cognitive activity, the work is suggestive of the idea of cognitive transfer from one person to another through various forms of mediation. The phrase "mental image" is used frequently during the discussion and also in supporting materials related to the exhibition, referring to the representations that appear on the screens of the exhibition. Additionally, the use of neural networks is suggested as being connected to the human imagination. The fact that the images in this work have been graced by AI is fetishised, overtly relying on the concept of AI to imbue what are, on their own, fairly uninteresting images with greater importance.

Huyghe's commentary on the work asserts that such forms of mediation may endow humans with new modes of connecting with the nonhuman. The artist asserts that his work is not for "us", alluding to a similar relation between human and nonhuman. He regards his work not in terms of exposing something to an audience, as art is traditionally thought of, but rather as an act of facilitating an exposure of the audience to "something" (Serpentine Galleries 2018). This not only raises issues regarding the cybernetic systems this view relies upon, it also touches on notions of intelligence in regards to the human and the nonhuman.

The artist has described the work as communicating an idea between human and nonhuman through thinking:

> It is an instant of collective production of imagination between two types of intelligences, human and artificial. Human imagination has been externalised without the subject predetermining the outcome, bypassing all modes of expression such as language or the senses, and is visualised using a brain-computer interface. (Serpentine Galleries 2019)

To think of this work in terms of the Umwelt concept, we must first enquire as to the subject in this case: the Umwelt of whom — or of what — are we considering? Could this refer to the droves of human visitors who visit the space on a daily basis? Should we focus on the nonhuman elements of the exhibition: the flies, sensors, or screens? Or is this representative of the Umwelt of those involved in the creation of the work?

Regarding the nonhuman dimension of *UUmwelt*, Huyghe explicitly makes the case that human audiences are not his primary concern, touching on the autonomy of image-making systems — and their products — from humans. He makes the following comment during his interview with Hans-Ulrich Obrist: "The work does not need the public. It's not made for us. It's not addressed to us. It doesn't need the gaze to exist. It can live its life as a work without that need." (Huyghe 2018)

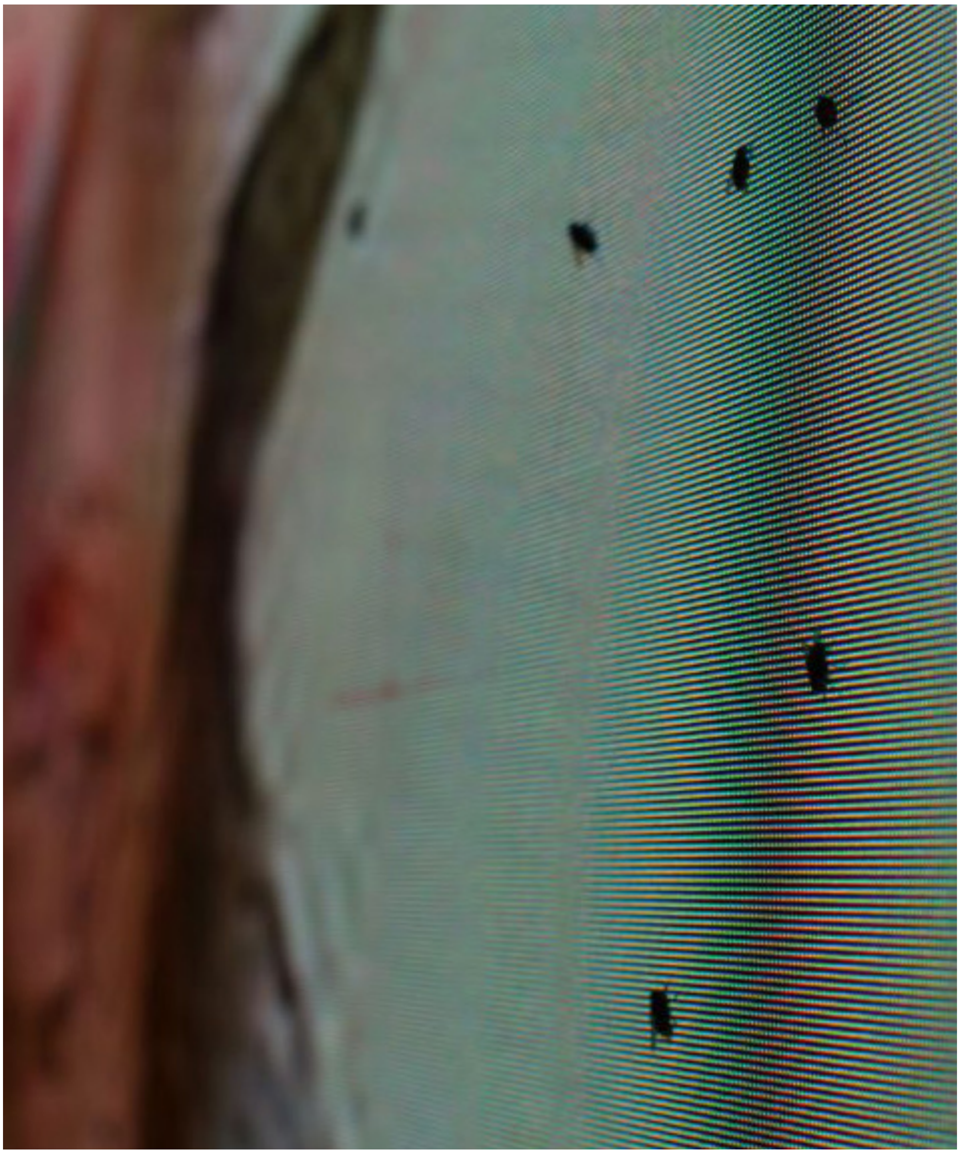


Fig. 66: Installation view of *UUmwelt*, detail of screen with flies. (Huyghe 2018).

Considering machines as interpreters and producers of visual information, such as in instances that could be considered operative images, frequently brings up differences between the visual processing of humans and that of machines. One of the defining aspects of the concept of Umwelt is that the perceptual worlds of different beings do not necessarily coincide with one another. There may be situations of overlap between different perceptual systems, while they may also be, as Agamben puts it, “absolutely uncommunicating” (2004, 42).

But if all beings are locked in their own perceptual worlds, how may one ever become aware of the perceptual world of others? Trying to engage the Umwelt of an AI, if this is what Huyghe is trying to achieve, is a troublesome idea in the sense that it is looking toward an intelligence that is itself defined by the human. Machines now participate in the interpretation and creation of visual information to such an extent that the technological mediation of perceptual experience is often an integral part of the human Umwelt (Lee 2018). This may even be the case to such an extent that it comes to be seen as naturalised.

To disentangle a work of art from the human gaze requires overlooking many of the legitimating structures of art. The first of these is that by virtue of labelling something “art”, or an image for that matter, one is placing it in a particular relation to the world and calling for it to be viewed — metaphorically or literally. The artist’s explicit statement that the work does not need the audience to exist brings up a number of questions regarding the status of machines and the art object. *UUmwelt* (2018) was created by one of the world’s most acclaimed artists Pierre Huyghe, presented in the Serpentine Gallery, and discussed with the internationally famous curator of that space, Hans Ulrich Obrist, in front of an audience of hundreds of visitors. If an artwork were ever to be indifferent to its audience, it would be difficult for it to do so in such a high-profile context constructed around visibility.

Yet, if we are to treat this idea with the seriousness it deserves, the technological side of the piece is also in need of scrutiny. At every stage of the process, the technology employed has been tailored to fit human perceptual, communicative and representational norms: language, fMRI, GAN, and photographic digital media on screen. Visual media have been tailored precisely to the human perceptual framework that even nonhuman photography (Zylinska 2017) is anthropocentric to the extent that the very human parameters of visual technologies are so embedded as to efface themselves. The fact that it can be overlooked that digital video may be framed as anything other than human attests to this, raising the question of whether there are anything other than human-centric modes of communication and mediation.

The feedback loop between technological mediation of experience is mirrored by the presence of various sensors throughout the exhibition space, which affect the display of the images based on the presence of viewers. These appear to contradict the idea of the work as apathetic to viewership and instead support a conception of the machine as indifferent to the actions of humans but nonetheless influenced by human activity. At the same time, this does indeed add to the feeling of the artwork as an ecosystem, a complex system of reacting elements that in a sense may take on a life of their own.

> You set conditions, but you cannot define the outcome, how a given entity will interact with another… there is a set of elements, the way they collide, confront and respond to each other is unpredictable… I don’t want to exhibit something to someone, but rather the reverse: to exhibit someone to something. (Huyghe 2018)

The Umwelt is constructed as a contingent connection between sensory perception and the capacity of an agent to act upon that input. This is illustrative of the role played by technology in acting as an intermediary between human sensory perception within the technological production of images. For our purposes, this refers to what can then be understood as a contingent relationship between human vision and the interrelated expressions of agency and perceptual mediation exerted by human and machine within a perceptual encounter.

The human Umwelt is often mediated by technology, extending the abilities and sensory capacities through the use of technical apparatus. We recall that technical mediation of perception tends to augment sensory perception while also altering it in the process (Ihde 1990). That is to say that, while a perceptual technology may improve or amplify a sensory experience, it does so while imposing a particular interpretation of that experience through the technology implemented.

The projects and ideas discussed in this and the previous chapter demonstrate various perspectives on the ways in which images produced using ML relate to, simulate or interact with human vision and agency. Rather than considering them in a one-to-one fashion, as direct stand-ins for biological vision or authorship in image-making, we understand from this exploration that there is a much more complex entanglement between visual technologies and sight.

Framing ML-produced images as primarily the work of machines typically overestimates the role of computers, with one of several goals in mind. One of these is to propose such images as the product of machine intelligence, in which case they may be seen as inherently more or less valuable, based on whether such a system of appraisal views computers as capable of genius and authority. Technologies are often given either too much or too little credit for their performance, framing them as more powerful or more autonomous than they truly are. This is the case in both techno-positive and techno-pessimistic views, which interchangeably view technologies as overly capable or under-capable of the tasks they propose to perform.

In this sense, notions of image production, including those proposed by artists working with ML, reveal an enduring cultural preoccupation with the role of technology in art. This, much like theories of the image itself, remains unreconciled, without consensus concerning what it means for machines to produce — or to interpret or analyse — images. The technical dimensions of visual art remain tied to two competing notions: that of technique as in method and the of technique as in skill or virtuosity. Technological image-making may situationally be a means to an end, or it may meaningfully contribute to the work's interpretation. But determining which is the case in a given visual artefact is also highly contextual. For example, using analogue photography today has different meanings than it did 10, 50 or 100 years ago. In similar fashion, the use of ML and AI in art has different significance now than it did when Cohen first began working with AARON (1973–2016) (p. 79–80).

Far from acting as a one-to-one stand-in for human vision, the computational nature of MV at times proves fairly brittle. A given ML system may be extremely good at performing, image classification, for example, but may be prone to error due to a variety of engrained design problems such as engrained human bias. Working with data, as we understand from the previous two chapters, entails a great deal of decisions, which ultimately affect the outcome of algorithmic processes. For this reason, we now look at how the analysis of data can be used in various different ways.

## 5. Data and Representation

In similar fashion to the operative image (p. 96), which encourages thinking about images not in terms of what they look like but in terms of what they do, many artists have considered the complex processes and histories behind the visible surface of an image. While analysis of images employing machine learning (ML) may become highly developed, there are aspects of images that are contextual, external to the image itself. In the same way that images involving optical tricks may be seen in more than one way, images in general tend to have multiple avenues for interpretation. The use of ML as a way of producing simulations making sense of data has been employed by a number of artists, ranging from approving to critical and even comical. It also touches on the fact that data may be interpreted in many ways and is therefore less reliable than it may appear on face value. With this in mind, we approach the mediating role played by ML in the generation of images and its influence on the resulting interpretation of those artefacts.

### 5.1 Deconstructing Representation

Fig. 67: *Deconstructing Representation* (Lee 2019b).

Addressing the visual mediation of data, *Deconstructing Representation* (Lee 2019b) employs ML as an explorative approach to interpret and to visualise patterns within a dataset of images. The goal of the project was to see what happens when a dataset of images is subjected to interpretation by a DCGAN. For this purpose, I adapted a Pytorch DCGAN tutorial (Inkawhich 2017) and trained it on a dataset of my own visual source material, which was compiled by downloading all images saved to my Instagram account. The resulting images were then composed into a larger image with the earlier outputs on the left and later outputs on the right. This allows all outputs to be viewed at once and allows the viewer to follow the training process of the DCGAN from its early stages, at the left side of the print, to the end of the process, at the right.

**Fig. 68:** Detail of *Deconstructing Representation* (Lee 2019b).

**Fig. 69:** Installation view of *Deconstructing Representation* (Lee 2019b).

The work shows the gradual build-up and breakdown of computational representations and visual affinities. What one sees when looking at this work is a progression from visual noise, produced at the early stages of the training process, which gradually becomes more distinct and reminiscent of real-world objects before finally dissolving into over-saturated, overly-contrasted, indistinguishable images. The algorithm determines what will be visualised and what will not, interpreting patterns within a dataset into new images.

The project acts as a reflection on ways of making sense of unstructured data using ML. Rather than using a structured dataset in order to train a model to learn representations from similar images, the use of a highly unstructured dataset seeks to force the analysis of indirect patterns. This means that instead of training a model to create successful representations of different kinds of images of a particular class, it is hoped that by employing diverse images it will enable unexpected affinities to be found or developed between aspects of the original dataset. Automating processes of interpretation of data also seeks to build a cooperative interpretive process that functions in balance between my own artistic and aesthetic sensibilities and the processes performed by the computer.

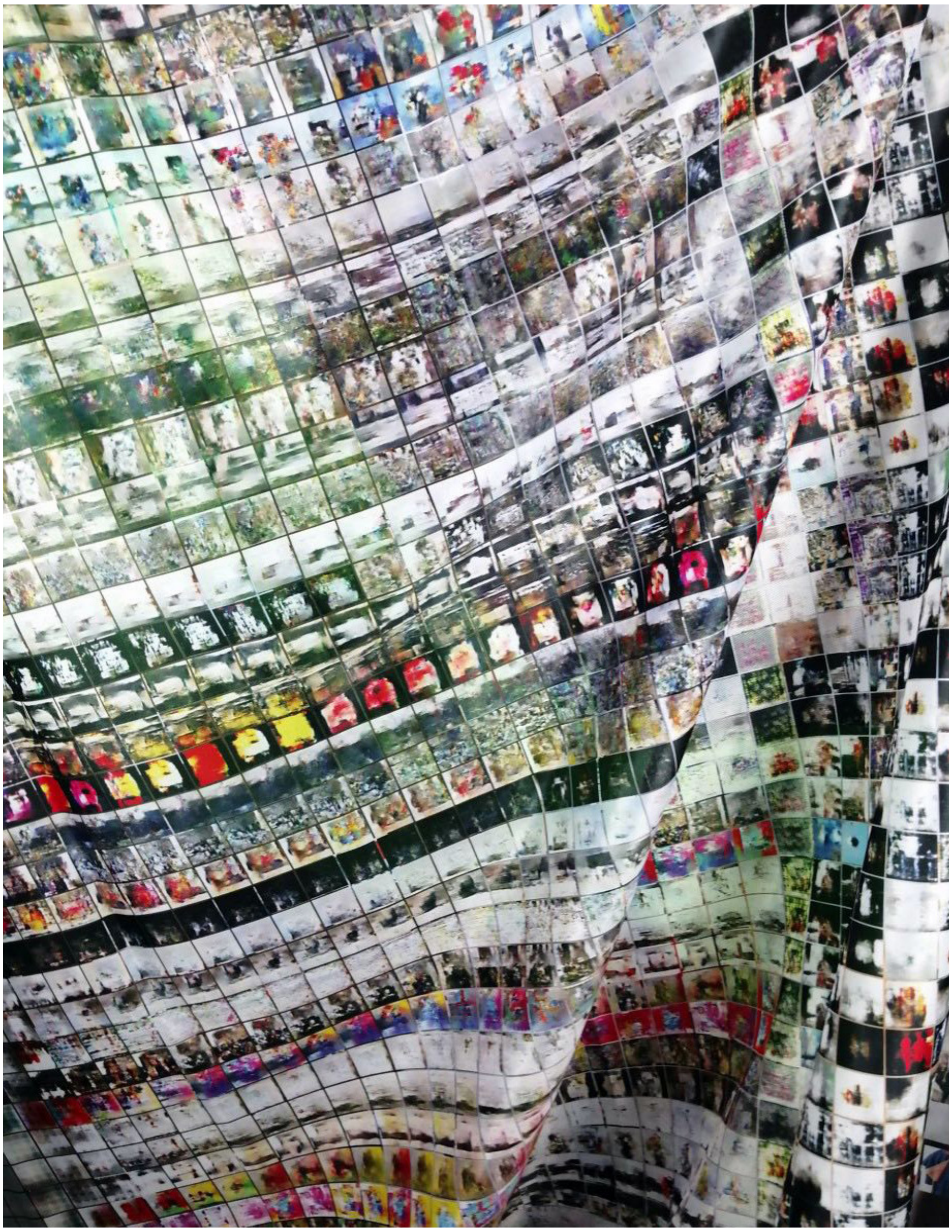


**Fig. 70:** Detail of *Deconstructing Representation* (Lee 2019b).

What ML contributes to the process is the performance of a computational interpretation and creation of images based on an initial dataset. This has to do with using the generative model as a tool to derive less human-directed insights from an initial set of images. In a similar sense to the aleatory practices employed by artists and poets over the course of the 20th century, this kind of approach seeks to use technology in such a way as to mediate perception but is less specifically concerned with the individual outcome. This experimental exercise is mostly concerned with revealing aspects of how the model functions through the way it performs the task at hand. Thus, the output images may have their own inherent aesthetic qualities, but they are also deeply linked to the process of their production and to the interpretation of a dataset into attempts at reproducing it.

### 5.2 The Illusive Quality of Images

The lack of fixed interpretations of images also comes into play in the difficulties that have arisen in attempts to police the circulation of particularly troublesome kinds of images in digital milieux. Many companies, including Facebook and Twitter, have faced increasing scrutiny for their failure to detect and to restrict the posting of manipulative content, as well as their refusal to restrict hate speech on their respective platforms.

Contributing to this challenge is the fact that a given symbol, or a given word, may take on radically different meanings, depending on context. What's more, these meanings are themselves highly mercurial and may change rapidly and unpredictably. For example, the Pepe the Frog (2005) character, originally drawn by Matt Furie as an apolitical comic, was appropriated first by far-right hate groups in the US, and then, naïvely, as a cute mascot for protests in Hong Kong in 2019. These radically different meanings that became associated with the same image of a green cartoon frog demonstrate how symbolic meaning has to do with other factors than visual appearance. Attempting to detect and prevent the circulation of hate speech by censoring images including green frogs would be very difficult to do without stifling the posts of political protestors using the same symbol for a different reason.

Similar issues come up in the #Freethenipple (Esco 2012) campaign, in response to censorship of female nipples on social media platforms. While the intention of that censorship was to prevent the circulation of pornographic images of women, the result has been received as an oppressive move against women's bodies and expression. Numerous workarounds have been developed for this problem, including photoshopping male nipples onto the female nipples in an image, to prevent detection and to allow the posting of images that contain female nipples.

These issues are especially critical given the current media landscape, often labelled as "post-truth", within which it is commonplace to sling allegations of "fake news" regardless of truth-value. In practice, misleading images may still have a potent effect in the world, in spite of being fabrications. Measures such as watermarks or verification by websites, education about the potential for spreading false information on social media and unscrupulous news outlets may be helpful, but determining the authenticity of an ML-generated artefact remains an issue. Given the lack of materiality of data-based images, forensic analysis of such artefacts often comes down to scrutinising data and metadata, and not necessarily on the visual dimension of media artefacts.

**Fig. 71–72:** Detail photographs showing the two opposite ends of the exhibition hall in *The City of Broken Windows* (Steyerl 2019b). Photographs (Lee 2019).

The potential for differing interpretations of visual content also speaks to the ambiguity inherent to representation. Not only is there a variety of different schools of thought as to what representation is, there are also many ways of enacting them. Steyerl's *The City of Broken Windows* (2019b) depicts two opposing regimes of representation — that of perfect verisimilitude and that of symbolism — through a tale of two cities: the city of broken windows and the city of unbroken windows. In the city of broken windows, artificial intelligence (AI) is used to detect and monetise the sound of broken windows, in reference to "broken windows" policing, a conservative political policy that asserts that fewer broken windows in an area will lower crime and increase property values. The city of unbroken windows, for its part, seeks to preserve its wealth by covering up broken windows with paintings. This is representative of the symbolic capacity of paintings to act as a stand-in for other things, whether or not they are believably realistic.

The two polarities of *The City of Broken Windows* (Steyerl 2019b) are demonstrated especially well in two components of its large-scale installation. At one end of the exhibition hall, a large plate glass window with a gunshot through it represents the city of broken windows; at the other end, a boarded-up window is painted to appear as if it is whole. Each demonstrates a different ideal of value, and also of aesthetics, which form opposite sides of the same coin, so to speak.

Taken to its furthest extent, verisimilitude in representation brings us to the interplay between map and territory, problematised by Jorge Luis Borges (1946, 325) in a fable recounting attempts to plot the most accurate map possible of an empire, escalating to the production of a 1:1 scale “map” of the very empire itself. This leaves us with the problem of redundancy, placing the upward limit of realism somewhere before the veritable recreation of the original object of representation itself. For example, the ultra-high-resolution *BigPixel* (Big Pixel Team 2019) image allows viewers to zoom seemingly endlessly into a bird’s eye view of Shanghai. While it may be to some degree a technological marvel, it is easily reduced to a gimmick.

But interestingly, the fact that images do not have a one-to-one relation to reality is key to their ability to function as representations. According to Anna Nacher (2016), the very act of pointing at the world, a foundational attribute of the representationalist paradigm, assumes an ontological divide between the image and its referent. That means, for example, that if a given object is represented in an image, its portrayal is implicitly understood as separate from the thing it represents. We therefore arrive at a delicate balance in representation: the image must be distinguished from what it portrays, yet maintain a relation to that referent, whether comprehensibly or not.

> How a drawing looks isn’t what it logically means. (Morton 2018, 93)

In cases in which an image bears little or no visual resemblance to what it is intended to represent, the process involved may play a defining role in mediating that referential connection, in lieu of visual likeness. The referential capacity of ML-generated images is often taken in a pragmatic sense in technical contexts: quantitatively measurable and reliant on its performance. What this means is that the experiment-based approach of computer science (CS) of applying discriminative and generative ML tasks involving images must be falsifiable in order for the exercise to have any efficacy. That is, the results must be testable, and if the measure of that testing is computational, the image is tested in a quantitative fashion. This is demonstrated well in adversarial examples, which can be made to be consistently categorised as a given target class, that may or may not align with the image’s human-designated — “correct” — target class.

But while an image may not conclusively be said to be necessarily “of” a particular class of item as opposed to any other on a computational level, in practice an image may be agreed upon to represent that image class with a high degree of human consensus, or certainty. The difference between one class or the other —computationally, or based on human consensus — is not necessarily connected to any inherent essential qualities of a given image. While ML systems may be made to effectively categorise or to generate images fitting particular image classes, the question of whether or not an image “is”, conclusively, one kind of thing or another, comes down to human consensus. This is especially the case as generated images have only a tangential relationship to their referent, if they are referential at all.


**Fig. 73:** *Name one thing in this photo* (melip0ne 2019).

For instance, in the circulation of “real or fake” memes on the internet, viewers are challenged to determine whether an image has been doctored or not. Often such images contain elements that are either visually or conceptually ambiguous, even presenting a form of visual paradox. In similar fashion, the example in fig. 73 confronts the viewer with a photographic image that does not contain a single identifiable object. Its caption prompts viewers to name one thing that is represented in the image, which at first appears to be a simple task. But although it contains many familiar attributes, it is not composed of differentiable objects.

The collective, Forensic Architecture, works with data-based images in a way that also reveals the fine line between appearance, the real, and the fabricated. The group researches, for example, how spatial information may be visualised in such a way that it may act as a form of evidence, especially in the context of human rights cases. In order to address the problem that there is often a lack of physical evidence of human rights violations, Forensic Architecture develops and implements digital methods and tools, which can help maximise whatever documentation exists regarding a given incident.

In *Computer Vision in Triple Chaser* (Forensic Architecture 2018), for example, witness testimony and a small number of teargas canisters gathered from the scene were the only proof of the alleged illegal use of teargas on migrants at the border between the United States and Mexico. Sorting through videos that could potentially prove what had occurred proved a daunting task, and not enough documentation existed in order to train an ML system to automatically detect the teargas canisters.

Therefore, Forensic Architecture used the existing canisters to produce simulated training examples, or “synthetic training data” (Harvey and LaPlace 2018), using the Unreal Engine.[1] These enabled a search engine to be developed, which was designed to detect the particular teargas canisters in question in video footage. In this case, simulation is used as a way of procuring evidence of actual events, rather than acting as an imposter attempting to stand in for the real. Much as we have seen before in other projects, the methodology and approach to the interpretation of data also plays an important role in its relation to events and objects in the real world. Forensic Architecture’s simulations are thus informed projections about actual situations based on known facts and data.

1: A powerful game engine, or software environment for video game development. (Epic Games 1998)

Fig. 74: *Mosaic Virus* (Anna Ridler 2019a).


Fig. 75: *Myriad* (Anna Ridler 2019b).

Anna Ridler's *Mosaic Virus* (2019a) (fig. 74) demonstrates another facet of the curious relationship between real-world objects and images generated using ML. To create the work, Ridler meticulously photographed 10,000 actual tulips (Shown in *Myriad* (Ridler 2019b), fig. 75), in order to produce the dataset a model was trained from. The resulting images of flowers are believable, although their relation to actual flowers is highly mediated. Similarly, thispersondoesnotexist.com (Wang 2019) generates photorealistic digital images of faces of non-existent people. This points out the illusiveness of generated images, and how well they can simulate appearances. These likenesses embody Baudrillard's (2010) concept of "*simulacra* of simulation, founded on information, the model, the cybernetic game-total operationality, hyperreality, aim of to tal control." (121) Instead, they are akin to the example of Ptolemy's maps, based on the compilation of numerous measurements of the world, and orchestrated according to the computation of data based on sets of instructions. As such, a single generated image of a tulip is based on far more information content than is contained in a straightforward digital photograph of a tulip.

**Fig. 76:** Deepfake of Steve Buscemi's face on Jennifer Lawrence's body (Unknown 2019).

Deepfakes[2] are notorious for the way they demonstrate the fine line between artistic expression and the manipulation of appearances. The technique allows the face of one person to be substituted for that of another, animating the person's facial features as if controlling a puppet. The deepfake technique was quickly adopted by internet users for what may be considered the obvious applications for such technology, making videos in which public figures appear to say or do things they would not be expected to, for example, splicing the faces of celebrities onto the bodies of actors in pornographic films and manipulating the words and actions of political figures. Often technical issues make deepfakes easy to spot, but the potential danger that deepfakes pose within visual media is that technical improvements may blur the boundaries between real and simulation.

While deepfakes and other forms of algorithmically-generated visual media may present new possibilities to facilitate the fabrication of believable images, this is ultimately an expansion of already existing possibilities to modify visual content. It plays upon expectations for images to be truthful representations of reality in spite of the fact that they merely act as mediators of visual perception and representation.

2: Which are now synonymous with the username of a Redditor known for posting them, "deepfakes", c. 2017.

ML has also been used as a speculative methodology for analysing the oeuvre of an artist and projecting patterns from the findings or to tailor the production of images to the statistically determined aesthetic preferences of an audience. The research project *Next Rembrandt* (2016), speculates on what the next painting of Rembrandt van Rijn may have looked like, had the artist lived — and painted — longer. The process of creating the image involved intensive interdisciplinary research, which paired qualitative art historical knowledge with technical expertise. The resulting portrait is a projection based on a statistical analysis of Rembrandt's existing paintings. A dataset was amassed from digital images and 3D scans of Rembrandt's known works, which were analysed to determine the most likely qualities a painting by Rembrandt would have: "a portrait of a Caucasian male with facial hair, between the ages of thirty and forty, wearing black clothes with a white collar and a hat, facing to the right." (The Next Rembrandt 2016).

The gender, age, race, dress and social status of the average sitter Rembrandt painted does indeed owe much to the context in which he lived and painted. Yet, generating an image from these tendencies does not produce new knowledge. Given that art has historically been a demonstration of the wealth and power of its patrons, it's hard to consider *Next Rembrandt* (2016) as anything other than a similarly biased reflection of wealth and power, as it is financed in large part by a bank (ING) and a software company (Microsoft). This is cause for concern because it allows the configuration of past and present wealth and power to stake claims on the reformulation and interpretation of culture.

While it is based on data, the hypothetical exercise of attempting to produce the next Rembrandt can neither be validated nor authoritatively discredited. It is the result of informed speculation, yet it is framed by its creators as the result of what would happen if the great master could "be brought back to create one more painting" (The Next Rembrandt 2016). As such, the portrait begs the question of whether a similar exercise may be performed upon the oeuvre of any artist, living or dead, rendering the artist obsolete.

Not only does this further complicate the question of authorship of ML-produced artefacts, but it also reduces the life's work of an artist to a visual style. One victim of this has been Vincent Van Gogh, whose paintings have been appropriated, using style transfers, to many netizens' snapshots to imbue them with a *Starry Night* (1889) style, for example. Reducing art to the level of a visual filter or style that may be applied at will risks missing a great deal of what is at stake in an artwork. A Van Gogh-styled selfie loses some of the qualities that make his original paintings significant, materially, aesthetically, and in terms of the context within which they were produced. This also assumes that what is at stake in an image is primarily, or even solely, visual, in opposition to the procedurally oriented images discussed previously.

While ML provides a wealth of digital tools for image production or modification, many of them do not go any further than providing what may be categorised as visual effects. For the same reason that photography was initially regarded as a lower art than painting, allowing anyone with a camera to create a realistic image, tools such as digital lenses and filters do not go further than applying a particular style to an image. Style, in this sense, can be understood as a generalised combination of visual attributes, which may then be applied to existing content.

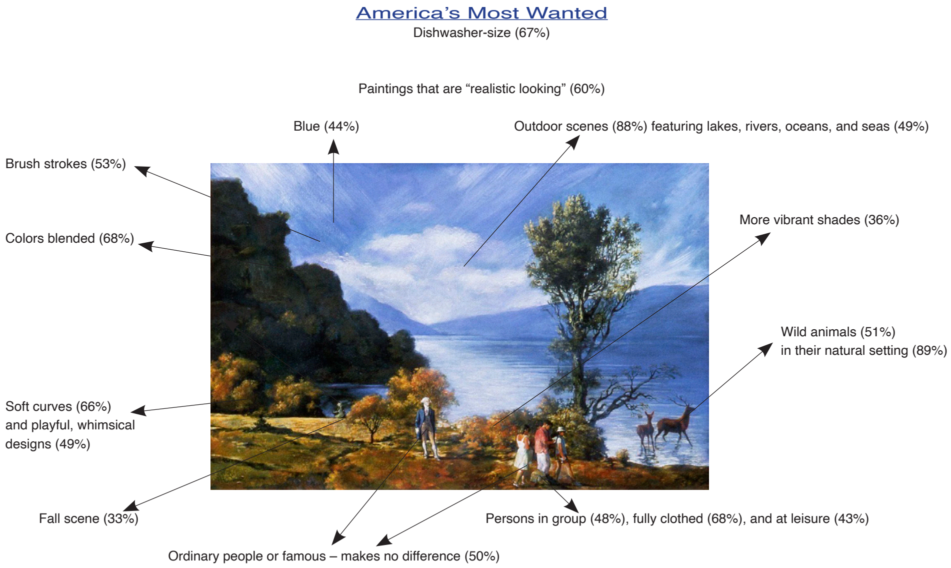



Fig. 77: *America's most wanted painting*. (Komar and Melamid 1994).

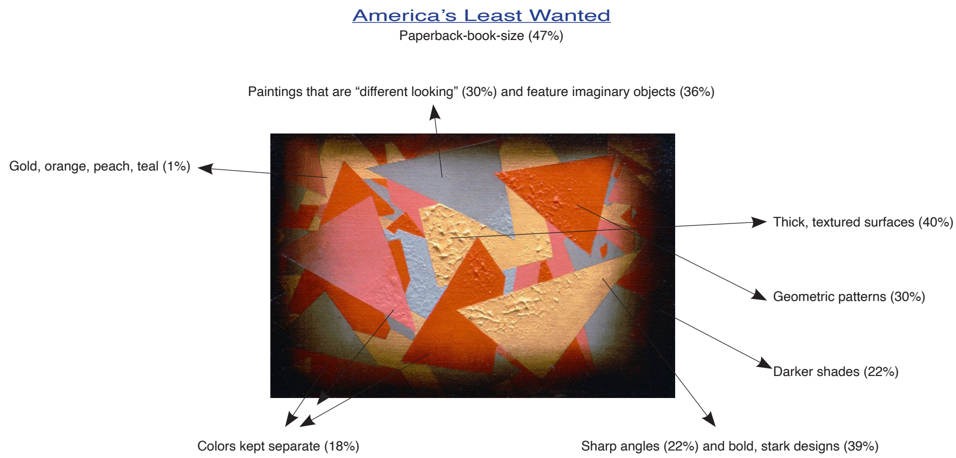



Fig. 78: *America's most unwanted painting*. (Komar and Melamid 1994).

Because of the degree of research involved in the production of *Next Rembrandt* (2016), it qualifies as more than the vacuous application of a style, but it is nonetheless unwittingly reminiscent of Komar and Melamid's (1997) take on scientifically determining the creation of art. The duo produced what they deemed the "most wanted" and "least wanted" (1994) paintings based on the results of opinion polling. The artists commissioned surveys through a professional marketing agency in order to develop statistics regarding the personal tastes of the inhabitants of various countries. This included the use of simple questionnaires regarding visual preferences and dislikes in regard to colour, style, and subject matter. The artist duo then produced a pair of paintings for each set of preferences representing a given country, purporting to reflect what each nationality wants most and least in paintings.

The results make an effective counterexample to the idea of producing an art based purely on the averaging of opinions (see fig. 77–78). Komar and Melamid show, in tongue-in-cheek fashion, how reducing art to a formula may reveal something other than an average image. The "most unwanted" paintings, indeed, tend to be bad in a sense most people could agree upon, but the "most wanted" paintings, themselves, are innocuous, erring on the side of hilarity with their trite subject matter and clumsy, formulaic compositions.

American respondents, Komar and Melamid concluded, tended to "prefer, for instance, traditional styles over more modern designs; they also express a strong preference for paintings that depict landscapes or similar outdoor scenes. In addition, most Americans tend to favour artists known for a realistic style over those whose artworks are more abstract or modernistic." (Komar and Melamid 1997). The resulting pair of paintings oppose a banal pastoral scene and a composition of garish colours, reminiscent of many avant-garde paintings from the early 21$^{st}$ century. The dichotomy it presents is extremely polarising, limiting the scope of art to what the majority of people can agree upon at the disavowal of art desired by statistically fewer people.

While the illusive capacity of images is inherent to their role as signifying media, the modalities of the influence of ML on images takes this to a high degree. In the case of projects such as *Next Rembrandt* (The Next Rembrandt 2016), the image produced involves the analysis of vast amounts of qualitative and quantitative information, which is performed by both humans and machines. Yet while the end result is the product of a great deal of informed analysis, it remains a speculative projection. Projects such as Komar and

Melamid's tongue-in-cheek attempts to create appealing and unappealing images based on tendencies identified through opinion polling playfully undermine blind confidence in data-based approaches to image-making.

### 5.3 Speculative Images

In spite of the fact that ML has shown to err on the side of reinforcing, not eliminating, bias (Aga 2019), it is often framed in terms of a presumed neutrality — and autonomy — on the part of the machine. This issue is of central relevance to reconsidering the assumed veracity of photographic images, and the role of the machine therein. Other examples, including Komar and Melamid's (1997) farcical attempts at scientifically deriving the most desirable and most undesirable images, lend an interesting contrast to projects such as *The Next Rembrandt* (2016), which espouse a genuine belief in the same endeavour.

It remains important to distinguish between the various processes and structures of visibility involved in image production and how they play out in the resulting images. Yet care must be taken not to impose existing hierarchical relations onto assessments of images. The mystique of ML and AI may lie in the fact that they are often regarded as highly "black box". Contrary to this perspective, while aspects of ML remain obscure, there is a great deal that is indeed knowable about the processes involved in using ML to generate images.

The necessity of monitoring the datasets behind ML systems becomes especially apparent due to the recurring issue of algorithmic bias. Basic assumptions which are built into ML approaches, such as basing predictions for the future upon data from the past, are also examined in critical light. This ultimately enables us to develop new perspectives on what ML-produced images represent – if anything – and how they relate to the interpretation of data.

Joy Buolamwini and Timnit Gebru (2018), Birgitte Aga (2019), Harvey and Jules LaPlace 2019, and Trevor Paglen and Kate Crawford (2019) are just a few among many who have demonstrated how bias may become embedded in ML systems. There may be a number of reasons for this, but a common problem is the use of datasets that are not representative of the data to be analysed. Many facial identification systems have, for example, demonstrated a systematic inability to recognise or to classify the faces of women and those with darker skin. This may be caused by the fact that the training datasets employed have proven to be statistically over-representative of white male subjects and, conversely, under-representative of women and racial minorities (Harvey and LaPlace 2019).

Situations of engrained bias consistently demonstrate the reiteration of existing prejudices, revealing a larger tendency in which ML has been shown to err on the side of reinforcing — rather than neutralising — existing dynamics. Not only does this lead to a lower degree of accuracy in the models that have been trained using biased datasets, for example. It also reflects the problematic assumption that the results of ML are scientifically accurate. As a consequence of embedded bias, ML has often been found to strengthen existing social and power dynamics, in which identity politics and socioeconomic factors may greatly influence an ML application from its design upwards. Many of its applications have proven to be highly biased, including so-called “predictive policing” (RAND Corporation 2013), algorithmically generated mugshots of suspects or the use of ML to determine whether individuals should be granted a loan. Each of these instances has not only proven to be inaccurate but also based upon the flawed assumption that the future will reiterate the past.

Aside from concerns of bias, many have pointed out the problem posed by the widespread use of ML for the purpose of surveillance. The use of biometric surveillance has been taken up by a number of artists (see Ch 3, p. 74) such as Harvey and Laplace (2019) as well as Crawford and Paglen (2019), who point out that personal data may be harvested without consent. The internet has made images easily accessible, often with few or no restrictions or barriers against misuse. Mass-harvested images from social media accounts, for example, can be used to train models in order to gather information on, and even politically target, individuals. The Microsoft Celeb (MS-Celeb-1M) database, for example, appears to target “journalists, artists, musicians, activists, policymakers, writers, and academics”, including many who are “even vocal critics of the very technology Microsoft is using their name and biometric information to build” (Harvey and LaPlace 2019).

ML is often used to make statistical predictions about the likelihood of various outcomes, based on existing data. For example, predicting the next item in a sequence is a common probabilistic task that ML may be used to solve. Given the sequence 1, 2, 3, 4 and 5, for instance, a model would be trained to predict that the next value in the sequence would be 6. Expanding upon the general idea employed in this quite simple example of sequence prediction, much more complex tasks may be achieved, such as the performance of classification or even generation based on an initial input. The latter approach has been especially popular for the purposes of text generation, but it is also applicable to images, taking one sequence of pixels and generating another sequence of pixels from it.

While it is logical to make conjectures about the future based on known information, it may also lead to a problematic feedback loop. By reinforcing statistical data, it can create a self-fulfilling prophecy: as it has been, so it will be. This approach also spills over into the increasing reliance on ML in wider contexts of decision-making, which in many cases have proven to be inequitable. Many applications in which real-world outcomes are based on algorithmic assessments, such as the much-debated use of predictive policing (RAND Corporation 2013), in “crime forecasting” or the algorithmic determination of bank loans, are rife with the possibility for inherent bias. The founding assumptions these techniques are built upon are highly problematic, and the association of demographic markers such as race, income, and location with criminality, in the case of predictive policing, has been demonstrated to overestimate the importance of these factors.

Many ethical concerns have come to light in which originate in the design and implementation of ML systems, but Luciana Parisi (2018) criticises ML and AI on a more foundational basis: the expectation for the world to be compliant with human logic. The logic of differentiation, which is exhibited in ML, Parisi argues, has also affected appraisals of value based on a similar logic of division, between classes, races, gender, kinds of bodies, and intelligence, which have been used in the service of socially oppressive practices such as colonialism.

In similar fashion to the expectations of photography’s association with veracity in images, discussed previously, ML has also been framed as having inherent truth-value due to the presumed autonomy — and therefore, neutrality — of the machine. She also asserts that there is a differential logic embedded in ML, which ultimately sways its outcomes towards that which may be easily differentiated, which can be credited to Rationalism. This is reflective of a turn away from expectations of deriving truth from faith towards deriving truth from reasoning. While this led to a great change in terms of the production and appraisal of knowledge, in some cases, it has proven problematic for merely presenting a displacement of a religious kind of faith — and also power — into science and technology.

This is related to the “two cultures” (Snow 1956) divide polarising science and technology from the arts and humanities. The kind of instrumentality and differentiation described by Parisi can be seen not only in the transformation of images into operative images (Farocki), but also in the finer-grained logic of differentiation that goes into determining the visual content of digital images generated using ML.

Fig. 79: *This is the Future* (Steyerl 2019c).

> But as the future was predicted, the present became unpredictable.
>
> …
>
> Prediction takes the place of production. (Steyerl 2019c)

The assumption that all things may be differentiated computationally, which is embedded in ML, also resonates with Hito Steyerl's (2019a) criticism of the reliance of ML upon "past data" to make predictions about the future. Steyerl has been a vocal critic of many aspects of AI, pointing towards the danger that lies in the tendency toward a normalisation of technologies of prediction. *This is the Future* (Steyerl 2019c) centres around videos of "future plants", flowers that have been generated to anticipate the growth of plants. But rather than producing images of new kinds of plants with unique characteristics, these are instead made from recombining and repeating components of existing ones. The seemingly otherworldly plants behave in ways normal plants would not, and, Steyerl mythologises, are endowed with special properties. The imaginary plants are grown to produce cures for the ailments of current society including social media addiction, brains susceptible to hate speech and austerity propaganda, poisoning autocrats and reminding humans to take time to do nothing (Steyerl 2019c).

Steyerl applies a similar approach in several other works, including the performance *Political Pyromancy* (Steyerl 2019a), in which the artist generates a video attempting to predict the movement of a flame a split-second into the future. The results of this experiment can be seen as a cautionary tale, as the flame disastrously spirals out of control. It is significant to consider the fact that although algorithmic approaches are able to produce new visual content, they do so by making conjectures from past content. This means that while they have a degree of novelty, it is restricted, effectively, to projecting the future from what has occurred in the past. The nature of ML, itself, hovers between the goal of prediction and its basis in previous data, meaning that the images created are in some aspects new, while also being reiterations of existing patterns.

In many instances, the use of adversarial approaches in art employs critical tactics, which respond to MV by adapting to its parameters. The structures of mediation, in this case, become the most visible attributes, while all others fade between visibility and invisibility. This involves getting to know these systems and attacking them from the "inside", so to speak, by adopting the kinds of registration on which they function. But an enduring issue is that the aspect of invisibility in technical systems makes it difficult to see, access, interpret or contest the structures at work in the media we interact with. For this reason, ML and AI systems are often referred to as "black box", overlooking certain obvious avenues to understanding their inner workings (Bucher 2019).

Kate Crawford and Vladan Joler's *Anatomy of an AI System* (2018) addresses this fallacy, exhaustively detailing the many hidden factors behind the seemingly innocuous *Amazon Echo*. Crawford and Paglen's (2019) *Training Humans* focuses on the history of ML training images and how they have changed over time. In the exhibition, training examples from the 1960s to the present are displayed, enabling human viewers to inspect and scrutinise the invisible images with which Paglen is fascinated. This visual material, not meant for human eyes, but rather intended to be processed by computers, also gives insight into the invisible power structures behind the collection of that biometric data.

One way to compensate for algorithmic bias would be to have more representative datasets, but, as Parisi (2018) has problematised, does one actually want to be included, and therefore better tracked? The desire for inclusion in more representative databases for biometric identification amounts to inclusion in more accurate and effective surveillance, control, and manipulation (Parisi 2018). Inclusivity, in the case of attempting to overcome the bias inherent to facial recognition technologies, would mean to have one's face co-opted, commodified, consumed into a database of other faces, all the better to track, trace and find them and others who look like them.

Rather than relying on existing datasets, some artists critique or bypass their embedded problems by constructing their own. In *Mosaic Virus*, for example, Anna Ridler (2019a) photographed thousands of tulips. Her work often centres on the painstaking production of bespoke datasets, which can also be seen in her piece *Fall of the House of Usher II* (Ridler 2017). One may also employ a tactical — adversarial — approach, arguing for the contamination of training data. This enables the accuracy of a system to be degraded by introducing error and polluting ML systems with incoherent data. The same idea has been used by activists to thwart data mining by providing their personal data along with useless data that they hope will render the data less useful.

Steyerl's (2019a) criticism of the predictive aspect of ML has to do not with ML as a technological approach but rather with the misplaced faith in it as a scientific — and therefore presumably accurate — projection. Treating ML as such, she argues, has the potential for dangerous consequences, as evidenced by the host of engrained inaccuracies and biases that have already come to light in connection with ML. The predictive aspect of ML assumes that the past is an accurate reflection of the future. The future may closely resemble patterns from the past, but this neglects — even hinders — the potential for change. Additionally, certain phenomena are more easily modelled than others. Simply because ML may produce accurate models of given phenomena does not ensure its ability to function accurately for other applications.

The unstable relation between images and data, which is examined in this chapter, demonstrates how easily data may misrepresent, falsify or distort appearances. While ML may act as a tool to enable statistically informed projections to be made, there are many factors that determine its accuracy in doing so. Deepfakes make this especially apparent, by using ML to manipulate visual content. In other cases, such as basing predictions about the future on events of the past, it is the logic of the process, not so much the express intention, which causes inaccuracy. This is the case in many situations of proven bias in visual applications of ML, but it may be more difficult to spot such errors in cases which are less obvious.

Visual representation is already a highly complex and nuanced topic, on which there are many conflicting viewpoints. In addition to the existing complexity of discourse on representation, ML offers its own representational modalities, in which what is visualised in images is a reflection of learned patterns in data, rather than a direct visual depiction of objects or ideas. This quality in images produced using ML bears a perhaps unexpected connection to the tradition of painting. It is commonplace, for example, for a single painting to be composed from detailed examination of its various parts, which are almalgamated into a whole which is equivalent to more than the sum of its parts. For example, in a still life painting, numerous studies of the objects represented contribute to a composite view of the painting's subject. And, recalling earlier discussion of the machine as artist, many of the master works of painting are attributable to workshops, as opposed to singular master artists.

This emphasis on the multiplicity behind, or in, ML-produced images offers an interesting lens through which to view what is at stake in images. Images may still function in traditional fashion, with straightforward representational relations between aesthetic and communicative qualities. But with the wealth of possibilities opened up, not only by ML but many other visual technologies as well, it is clear that what is visible on the surface of an image may not coincide with its information content. Just as it is possible to create an image that does not contain any identifiable objects, highly specific images can be produced, with no direct connection to reality.

## Conclusion

Recent explorations with machine learning (ML) in art contexts have probed various aspects of the image, posing thought-provoking challenges to existing discourse. These are examined from three primary angles, considering how algorithmic processes have led to a re-evaluation of how images are defined, how they participate in the mediation of human agency and perceptual experience and, ultimately, how images are interpreted. In the process of addressing these issues, various interrelated notions are explored. Not only does the highly automated, algorithmic nature of ML-generated images undermine traditional understandings of what images are, how they behave and how they relate to the world, but it also calls into question certain deeply-entrenched conceptual divisions between the human and the nonhuman, and the visual and the non-visual in the process. Instead of seeking to delineate aspects of image production into such categories, this thesis draws together aspects which cut across a variety of different visual media, and that enrich an understanding of the complexity entailed in current image cultures. To this end, a survey of relevant examples from interdisciplinary practices offers a wealth of different notions that shape the role played by images in contemporary art and how it is theorised.

New forms of visual technology have enriched understandings of the image over time by demonstrating its potential through a variety of diverse attributes. This is especially notable in the use of ML in the production of images, in which dynamic computational processes inform the resulting outputs. As a result, artists and theorists alike have recently emphasised a view of images which is inclusive of the performance of algorithmic procedures instead of primarily focusing on their visual qualities, as has traditionally been the case. But rather than negating or invalidating previously-held notions for the appraisal of images, technology has expanded the field to accommodate both new and old forms of visual media.

The development of algorithmic image production processes has brought about an important interrelation between images and data. Central attributes of how images are defined also underwent a shift towards considering the importance of process in addition to visual aesthetics, and towards the establishment of notions of images as scienticially accurate depictions of the world. This is reflected in the systematic production of images according to mathematical and scientific principles, involving the use of specialised apparatus and techniques.

Newer forms of image production highlight the processual, ephemeral quality of data-based visual media, which also sheds light on similar attributes in existing image-making techniques, which had been regarded according to different principles in the past. The image is made interchangeable with its transcription as a dataset, emphasising the perspective of the image as a view of the world based on data, treating the image and text, and the image and the world, as interchangeable. The relation between the image and measurements of the world is important to understanding not only the relation between the image and computational processes, but also the cultural assumption of technologically produced images as scientifically accurate representations.

Creating images from a studious and focused observation of phenomena in the world reflects an empirical view of the world. As we understand from looking at examples from long ago in comparison to the present, such a perspective caused an aesthetic change, as well as affecting the the way that images were viewed. For example, in the Renaissance implementation of linear perspective not only made images more compliant with the parameters of human vision, it also meant that they came to hold a position of being more accurate representations than those that are more symbolic. The appearance of images thus became more representative of the world as it is perceived by human viewers, as opposed to being an ideological representation of the world as we think it is or should be.

This also meant that images came to be considered forms of empirical evidence, such as in the case of crime-scene or biometric photography, which enabled images to stand as visual evidence of real artefacts or events. In ML, the blanket association of technological image-making with accuracy comes under scrutiny. Developing visualisations from data has the contradictory impact of encouraging a kind of realism that is deeply tied to technological mediation. Firstly, a great deal of human intervention is required in order to produce accurate or believably realistic results, contrary to the proposed autonomy of machines in processes of visual mediation.

The incorporation of optical principles into image-making technologies changed the role of images relative to human vision. This means that visual media have been designed to be compatible with human vision by implementing optical principles. Rigorous perspectival techniques systematically implemented geometrical relations between objects in relation to human, optical perception of space. This expanded upon the scientific perspective on the world, or the image, as a database (Hoelzl and Marie 2015, 96), to incorporate the perceptual apparatus of the viewing subject as a central component of the image.

By assisting in the exploration of visual possibilities and the synthesis and interpretation of data, ML enables novel understandings of the word “representation”. Forming an ML representation of a dataset, for example, enables the model to interpret new data in a desired way. It thus becomes a lens through which to interpret other information. What is remarkable about this is that it facilitates a statistically informed modality for the production of new visual content.

Tracing the integration of algorithmic processes into image production to much earlier examples, this research begins by examining how present visual media builds upon simpler techniques and modalities. The emphasis on the role of procedural and data-based approaches to the creation of images proposes a view of imaging technologies that is inclusive of analogue algorithmic processes that offer insight into the more complex processes involved in current visual media. By considering the way in which such processes have impacted understandings of the central attributes of images, we are better able to understand the foundations upon which current theories of the image are built. In so doing, the complexity of relations between the visual and the non-visual that arises in image-making is introduced and examined through a variety of examples. We also begin to consider how the execution of algorithmic procedures — either by human or by machine — influences how images are understood. Through an exploration of various technical approaches to the relationship between human vision and the visual processing tasks performed by machines, we develop an account of how visual media complement, augment and remediate visual perception, lending visual aesthetics that range from hyper-realistic simulacra to the non-visualised computation of data.

Treating the performance of visual processing tasks by machine as if it were autonomous from human agency has a long history. It lends itself to inaccuracies in how visual technologies and visual media are understood. Such notions tend to normalise either the human or the machine as the primary point of view. At one end of that spectrum, images are associated with expressions of the human intellect through visual media. At the other, autonomous machines produce images, which are indifferent to human agency, perception and values.

The diversity of visual artefacts falling between these polarities is at odds with theoretical tendencies that overestimate the degree of division between human and machine participation in image production. Considering images as the product of nonhuman vision and intentionality, as numerous theories have done, tends to overlook the important influence of human values have in shaping conceptions of the image. Whether this takes the form of considering images to be a reflection of human intellect and expression or of a scientifically accurate depiction of the world has a great deal of influence on the evaluation of what images are taken to represent.

The shared intentionality expressed through the use of ML to create images can thus be understood as a composite mediation of data through algorithmic processes but is ultimately understood through the parameters of human perceptual experience and understanding. It also underscores the interrelation of human and machine forms of intentionality, which is often minimised in theories that overlook the importance of the role played by humans. This falls at both ends of the spectrum between anthropomorphising and posthuman perspectives, but nonetheless prevents accuracy in discourse on ML-produced images.

This connects even highly technical image production processes in which, for instance, digital computers play a larger role in determining visual outcomes than older forms of visual media. There has been a noticeable tendency to minimise the role played by machines in image production, and this role is often treated as autonomous from human intervention or inferior to it.

Situations such as adversarial examples, or the great deal of evidence of inherent bias in ML systems, point out how much these systems are reliant on the subjective decisions of humans. This extends from the composition of datasets to the design and application of algorithms and the tweaking of parameters, each of which plays a vital role in the resulting images. Various approaches to that interpretation of data lend themselves to different results, as does the make-up of the data employed. This makes ML subject to a high degree of human intervention, primarily in the pre-production phase.

Not only are visual technologies inextricably tied to the human perceptual framework, but the degrees of mediation performed therein also make them subject to high levels of interpretive processes. Images are by design made to be suitable to the parameters of human vision. Visual media thereby enable us to communicate perceptually, but also conceptually, through the attachment of ideas and aesthetic characteristics.

Additionally, the degree to which images are intended to be interpreted by human eyes, as opposed to being deciphered through analysis performed by machines, colours their representational capacity. This contributes to a form of visual literacy in which assessments of images exceeds their visible attributes and entails the consideration of how a knowledge of the technical processes behind images adds to the way they are understood.

The popularity of adversarial approaches, especially centring on criticality towards the use of ML in biometric surveillance, is revealing of several important factors. Firstly, adversarial approaches acknowledge the complex interplay between human vision and visual processing tasks such as facial recognition, which are performed by machines. They also exemplify the capacity of technology to work against the expressed intentions for which it was designed. In this sense, this asserts a stance towards ML that has both the capacity to attack, undermine or elucidate its inner workings. In such a way, artistic use of adversarial ML approaches in image-making also visualises the processes that lie in the subface of images.

There is a persistent inclination either to consider highly automated image-making processes as autonomous from human control or to consider human ability the measure of machines. This is especially significant when considering the extent to which human subjective experience comes to define many aspects of how imaging technologies are designed, experienced and theorised. Rather than fitting into strictly defined categories of "human" and "machine" image production, the unstable interplay between various forms of agency in the production of images by, or rather, with, machines may be better described through more nuanced terms.

As a way of describing the at times conflicting yet deeply interconnected processes and modalities of MV as compared to human vision, the operational image plays a significant role in reshaping discourse on the image. Instead of holding a mirror up to the world, as many of the early visual technologies covered here have aimed to do, operational images act upon it. Prioritising the execution of spatial procedures over strictly visual processes reformulates what may be defined, ontologically speaking, as an image. By pointing to the lack of reliable relation between the image as a visual artefact, the process of its production and its representational capacity, the operational image runs counter to the association between visual observation and empirical evidence of reality.

The synthesis of data into images, such as in several of the examples covered in this thesis, demonstrates the variability of relations between representation and referent. Images do not always bear a direct visual resemblance to what they are intended to represent. If operational images may be understood as lacking a divide between being and appearance, post-representational (Nacher 2016) images may or may not bear visual resemblance to, or even point to, an identifiable referent.

Because algorithmically-produced images are highly focused on procedure over their visual content alone, this could be seen as causing a breakdown in the relation between image and referent. But such images do indeed convey referential relationships. What is learned in ML-produced images is governed not only by interfacing with an algorithmic system itself but also by the composition of data, which together serves as its empirical foundation. As such, ML facilitates an approach to the automated interpretation as well as the generation of visual information by inferring patterns in data. Rather than referring to individual objects — conceptual or physical — such images refer more to databases (Hoelzl and Marie 2015, 96). Representations and their referents are tied together not primarily by visual resemblance, but instead by data, technical processes and apparatus.

For example, in ML-generated images, the visual surface is not exclusively tied to representing a visual resemblance of a referent. It may instead champion the adherence to the execution of an algorithmic process. In such a case, the truth value of the image is tied to the method employed, more so than its visual appearance. This is key to the empirical role played by technically produced images, in which they are taken as reflections of reality informed by the scientific nature of their production process.

How this differs from earlier approaches to image-making is that ML contributes a greater degree of agency on the part of machines to determine visual outcomes. Yet the human in the loop plays a substantial role in structuring the potentiality of a generative system. Visual media such as digital photography may be automated, but they merely implement a straightforward program. ML is commonly understood to be capable of producing surprising outcomes, which are statistically difficult — even impossible — to accurately predict. But, as can be seen in several examples here, unpredictability on its own is not a sufficient criterion for the production of art.

In current theory on image-making, as well as artistic practice, echoes of deeply entrenched, yet unresolved, notions continue to arise in relation to the role played by various visual technologies. This includes the tendency to anthropomorphise machines or consider them as wholly autonomous from human influence, as well as other issues, like the belief in the inherent veracity of technically produced images by virtue of their relation to data. While they respond to important aspects of the technical character of current image-making, the uncritical continuation of these ideas leads many people to overlook crucial aspects of what is currently at stake in images.

ML contributes a new understanding of representation informed primarily by relations in data, instead of in terms of visual representations of objects and ideas. Such data may have variable relations to objects and ideas, but these are connected through levels of technological mediation. By no means neutral, it is rather a different way of approaching visual content. ML may therefore reveal different visual outcomes based on the modality through which visualisation occurs.

Applying ML thereby acts in an analytical capacity, influencing visual outcomes to a greater degree than in other forms of image-making that have a more one-to-one relation between input and output. Printmaking, for example, has a considerably more straightforward relation between its mechanism and the resulting image. But ML, and even early analogue processes that place higher degrees of control outside the direct agency of human image producers, enables machines and processes to play a greater role in determining visual outcomes.

How this differs from forms of visual media, such as photography, that prioritise verisimilitude, is that it instead prioritises the hermeneutic role of the computer to interpret visual information. The role of the images as a form of evidence thereby comes into conflict with its corresponding capacity for illusion. If it were not for images' capacity to deceive the eye, they could not act as simulations. This is in contrast to operational images, which do not simulate, but instead operate.

Acknowledgement of the speculative nature of technically produced images has a large presence in the sceptically oriented discourses of art and the humanities. But in spite of their criticality, these discourses nonetheless perpetuate some misconceptions as to what ML is, does and means. Technosceptical positions, while often pointing to valid concerns regarding a given technology, at times lacks precision as to whether it is the technology itself, or the constructs it participates in, which is at issue.

While image production involving ML differs in some respects from more traditional forms of visual technology, it nonetheless shares critical features with them. For example, the production of an image using a generative adversarial network (GAN) is in some ways more similar to the approach of painting than that of photography. In both GANs and paintings, a great deal of visual information informs the production of the image, while analogue photography captures a particular view at a given time. A GAN learns from given information and is able to then implement a working knowledge of what patterns of pixel values appear to humans as a face or some other kind of representation.

Artists working with ML in their practice have developed useful perspectives on how images act as intermediaries between human vision and the algorithmic procedures performed by machines. In so doing, these investigations expose the often-contradictory ideas that hold that technical modes of production both result in the image being a form of empirical evidence and are the product of nonhuman intentionality. These have arisen in relation to various forms of visual technology, often invested in the legitimation or delegitimisation of particular methods as opposed to others.

Artistic perspectives on this topic have contributed a rich understanding of the image, which accounts for not only the aesthetic but also the technological and communicative qualities of visual media. The artistic examples covered here are bound together by their focus on the interplay between aesthetics and procedure, exploring not only the aesthetic dimensions, but also the technological modalities of ML and their cultural significance. While they engage a variety of different media and technical approaches, each demonstrates an attention to how algorithmic procedures may impact visual outcomes. This extends from simple algorithmic approaches, which exhibit related modalities, to more recent forms of visual media and highly complex works of art.

Looking at practical examples through the lens of several different theories enables a rich view to be developed of the value systems at work in thinking about images. Across the spectrum of practical examples covered here, several themes arise repeatedly, which are linked to ongoing discrepancies concerning the role played by technology in image production. This includes the reformulation of images in terms of the execution of algorithmic procedures, the increasing role played by automation using machines, the interplay between human perception and visual media, and the interpretive processes involved in image production that arise as a result. Such themes act as axes in the evaluation of images, in which they come to inform visual and processual aspects of how visual media are in turn designed and understood.

The technical potential of image-making technology often leads to difficulty in discerning fact from fiction. In some cases, the potential of ML has been used in a highly scientific way, to produce visual evidence of situations in which only non-visual data exists. Using ML in an interpretive capacity enables the existing data to be understood in new ways, through the generation of images. It can also be used in a speculative fashion, to create informed projections about past or future events. Hard and fast distinctions, such as between truth and illusion or between human and machine intentionality and visual processing, are incompatible with the nuance involved in current image production. This means that certain aspects of visual media may challenge a given theory of the image while enforcing others, developing a heterogeneous view of the image.

The interpretation of images is tied to context, but also understanding of the technical processes involved. This means that ML-produced images tend to require higher degrees of technical knowledge in order to apprehend them than those in which the process plays a lesser role. There is a discrepancy regarding the importance of media to works of art, and whether the medium is merely a method for conveying the content or if it is also seen as an integral part of the message. The problem often boils down to a contention between revealing and hiding the technical conditions behind a work of art, and whether the technology is a means to an end or an end in itself. The gimmicks achieved by "black box" technology and the technology itself laid bare represent polarities between understanding how a visual technology works and appreciating its effect. These are, importantly, not exclusive of one another. For example, our enjoyment of a pre-cinematic optical trick may be increased either by not knowing what goes on "behind the curtain" or precisely because we understand how it works.

The history of art is filled with a spectrum of simulation and dissimulation (Baudrillard 2010, 3), but the kinds of visibility and invisibility brought about by ML images take this to higher degrees than in the past. There are layers of information in images that are mostly inaccessible to humans but that nonetheless play a substantial role in our visual media. For example, a simple pencil drawing on paper makes the process of production relatively accessible to viewers, and the average person would have a good understanding of the process involved. At the other end of the spectrum, generative adversarial network (GAN) images make the process relatively inaccessible, and the general public has little understanding of the process involved. The levels of mediation that occur between the surface of an image and its subface may entail variable degrees of interpretation, meaning that technical implements and methods may play a substantial role in determining the outcome of the production of an image without this being visually apparent in the final product.

Image-making technologies involve both visual and non-visual processes, and the combined agency of human subjects, with the technique or apparatus employed. Yet false dichotomies between visual and non-visual, human and nonhuman within image production continue to haunt current discourses. These findings ultimately support the conclusion that while ML offers certain novel capacities for the generation of images, theories have tended to overstate their differences from previous visual technologies. Focusing on the mediating role played by ML in the production of images enables the interrelation between visual and non-visual qualities of images and the participation of machines therein to be better understood.

Within art contexts, the modalities of the technology play a part in the artwork's meaning, to varying degrees. In more technically oriented projects, such as that of Klingemann's *The Butcher's Son* (2018) or the *Portrait of Edmond De Belamy* (Obvious 2018), the mystique surrounding the technology plays a large role in justifying its artistic merit. Such projects have achieved popular notoriety but have been generally snubbed by the art community for their lack of something beyond either highly developed visual effects or a perpetuation of the myth of the machine as artist (Broeckmann 2019). In other cases, the technique becomes integrated into the meaning of the work itself. For example, the work of the central figures explored in this research, Farocki, Huyghe and Steyerl, tends to consider how the function of visual technologies changes the meaning of the resulting images.

The separation of technical methods for the creation of visual content from their ties to human visual perception and intention often fails to address the deeply nuanced nature of visual media. While ML and other forms of highly automated image-making significantly alter the range of possibilities available for the production of images, they also remain tied to the referential quality of images. The point at which referential relations between images, data and the world become unintelligible to humans, either by being non-visual, illegible or otherwise inaccessible, poses a significant challenge to understandings about what significance they hold.

Grasping such problematic formulations of the image through such theories as the operational image, nonhuman photography, the Umwelt and others, we are able to relate better to instances in which human vision and intentionality play a secondary role, at best. Not only may images be orchestrated with little participation on the part of human perceptual experience, effort or mastery, but the ambivalence of such forms of visual media leave little with which to engage. We may challenge ourselves to conceive of the image without measuring it against anthropocentric value systems, but this tends to present itself as the conceptual limit for how we understand images.

Contrasting historical examples with those from the present enables us to understand how ideas surrounding current practices have been influenced by their precursors. It is particularly notable how similar ways of thinking about imaging technologies have endured over time in regard to quite disparate kinds of apparatus and techniques.

Looking at historical examples, we understand that cultural responses to visual technologies at their introduction varied from responses to them when they became more commonplace. The importance of the magic lantern, for example, was explicitly tied to its status as a public spectacle, in which the means of its orchestration were obscured from view. In the early days of photography and cinema, too, a lack of understanding of the processes behind images lent them a particular aura. Now that photography and moving images — at least in their digital forms — are extremely commonplace, there is a more normalised relation to such images, whether or not one has much knowledge of how such visual media work.

One may argue that the ubiquity of digital media acts as a factor in visual literacy with its artefacts, at least to the degree that most would ascribe their aesthetic qualities to the function of the apparatus involved, whether or not that function is accessible or understandable to them. For example, there is a growing popular understanding that algorithms affect visual media, especially forms of social media. While the exact processes are generally opaque to the average user of such media, they are nonetheless considered important when assessing images.

Taken together, the appearance of images and what we may call its technicity — among other factors — contribute to its overall appraisal. This includes contextual information external to the image itself, or not visually apparent to the viewer. Many works covered in this thesis reveal an attention to the relation between visual aesthetics and an aesthetics inclusive of the process involved. Overall, this may be seen as a procedural aesthetic, which champions ties between the visual and processual aspects of images. Such a view insists upon an interrelation between how images appear, how they are orchestrated technically and the combined meaning of these aspects. Current ML artefacts thus can be expected to change in significance as technological shifts occur in the future. And as ML becomes further normalised, for example, considering visual media in relation to its actual processes may enable the shedding of mythology related to misunderstandings of the processes involved.

Technologies of visual media, and the many ideas that have accompanied them, have been compounded over history, making theorising the image a complex endeavour. As we understand through the approach of media archaeology, technological artefacts are linked to larger tendencies that have played out over long periods of time. Traversing the history of image-making technologies enables us to develop a background against which to compare current visual media. The complex web of theories and practical examples covered in this research demonstrates the diversity of modalities and media though which an image may be articulated. While defining the image remains a complicated theoretical endeavour, we understand technological developments to have expanded, rather than drastically altered, understandings of the relation of images to their technological means of production.

ML can be understood as expanding, rather than fundamentally altering, understandings of the image. It adds to ongoing tendencies and technical developments which necessitate theorising images in new ways. This encourages focusing on the diverse and dynamic range of qualities images may take on, as opposed to treating them according to criteria specific to other media, such as painting or photography. Images produced using ML emphasise considering more than binary distinctions between visual and nonvisual, human and machine, perceptual and intellectual, instead offering insight into the interplay between these conceptual categories, which are engaged through current visual media.

## Continuation of Research

Moving forward from this research, I have several potential avenues to explore, including working together with other researchers and pursuing my own independent research.

I have been included as a named postdoc in a funding application to the Independent Research Fund Denmark (IRFD) for the research project *Playing with Data (PlayData): Visualizations as mediated interactions with data*. The project is organised by PI Assoc. Prof. Christina Neumayer with Assoc. Prof. Miguel Sicart and Prof. Irina Shklovski. If the funding application is successful, I will carry out a 2-year postdoc at the Department of Communication at Copenhagen University starting September 2021. My role within the research project is to organise a series of three workshops inviting artists to engage with how data visualisations might be created and deployed differently through artistic speculation. The output from these workshops will be curated into an exhibition.

I plan to continue to investigate how ML and AI shape discourse on visual media. The present research demonstrates the unsteady foundations upon which theories of the image and of art are grounded. Though we may conceive of images that do not comply with the rigid constraints of traditional conceptions of the image, art struggles to offer alternative structures that meaningfully depart from them. Instead of viewing this as a failure to deliver answers, I suggest that the entanglement between how we see, what we take it to mean and how images participate in perceptual mediation offer vital insights into visual culture as a form of knowledge.

In seeking to embody theories such as the operational image, nonhuman photography or the Umwelt in an artwork, one is met with the paradox that the structures inherent to artistic evaluation rely on the assumption that art is primarily situated in its sensible, communicative and human-intelligible attributes. Yet defiance of such traditions of art-making leaves audiences with little to grasp, raising several provocative questions including the following:

> Can an image be conceived of as invisible to humans, orchestrated entirely out of reach of our perceptual experience and understanding?

> Could such an image err on the side of hyper-visibility, in which viewers may perceive all an image has to offer on its surface, yet be unable to grasp any meaning from it?
>
> How do science and technology shape understandings of the production and visualisation of information?

I intend to continue examining these issues in greater depth concerning the interplay between the operational aspects of images, their execution and their presentation. In many of the artistic examples I have examined, there is a tendency to focus solely on phenomena that are visualisable or understandable through relation to human perception. For example, although much of the work that has been done with adversarial images focuses on their invisible qualities, the contrast of interpretations that occurs in such images is in fact visually understandable to viewers.

In similar fashion to the *PlayData* project, I intend to examine how artistic explorations offer insight into relations between data and its visualisation. Seeking alternative approaches to the problem of presenting invisibility within visual art, I would like to further examine how scientific methodologies act as a conceptual bridge between seeing and knowing. The emphasis that is currently placed on the technical and scientific dimensions of visual media offers insights into the view of images as a form of empirical evidence.

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## Abbreviations

| | |
|---|---|
| AI | artificial intelligence |
| AGI | artificial general intelligence |
| ANN | artificial neural network |
| CNN | convolutional neural network |
| CS | computer science |
| CV | computer vision |
| DCGAN | deep convolutional generative adversarial network |
| DNN | deep neural network |
| fMRI | functional magnetic resonance imaging |
| GAN | generative adversarial network |
| ML | machine learning |
| MLP | multilayer perceptron |
| MV | machine vision |
| NN | neural network |

## Appendix

In addition to the written thesis, numerous other research activities and outputs have contributed significantly to the overall development of this PhD project and to my own development as a researcher. Documentation of these components of the project are included here as a complement to the monograph. This includes a record of completed academic coursework and dissemination of research through talks, research papers, and exhibitions.

## Coursework

Intellectual Property Rights (IPR), Innovation and Responsible Conduct of Research, ITU, Copenhagen – 2,0 ECTS

Masterclass with Bernard Stiegler: “Simondon and His Notion of Information”, Aarhus University, Aarhus – 2,0 ECTS

Open Hardware/Open Machines, Aalborg University, Helsingør – 2,5 ECTS

Representation Across Fields, ITU, Copenhagen – 4,0 ECTS

Machine Feeling Workshop, Cambridge University and Aarhus University, Cambridge and Berlin – 5,0 ECTS

Artificial Life & Evolutionary Robotics: Theory, Methods & Art, ITU, Copenhagen – 5,0 ECTS

A Guide to a Successful PhD Thesis, The Royal Danish Academy of Fine Arts (KADK), Copenhagen – 5,0 ECTS

Presentation regarding conference participation (x3), ITU, Copenhagen – 3,0 ECTS

Total: 28,5 ECTS

## Academic Activities Completed Without ECTS

| | |
|---|---|
| 23/09/2018 –15/12/2018 | Research Stay Abroad<br>Under the supervision of Professor Luciana Parisi<br>Department of Media, Communication, and Cultural Studies (MCCS)<br>Goldsmiths, University of London, London |
| 14-15/11/2019 | *What is the Art in Artificial Intelligence? Workshop*<br>Center for Advanced Internet Studies (CAIS)<br>Bochum |
| 09/09/2019 | *Predicting Security and the Insecurity of Prediction Seminar*<br>Uncertain Archives Research Group<br>University of Copenhagen, Copenhagen |

## Dissemination of Research

### Supervision of Students

Supervision of 1 MSc thesis

Co-supervision of 1 BSc thesis

### Organisation

| | |
|---|---|
| 15/08/2018 –05/09/2018 | Hosting guest lecture by Søren Pold |
| 20/02/2018 –07/06/2018 | Digital Design Summer Seminar Planning Committee |
| 01/09/2017 –20/05/2018 | Politics of the Machines Conference & PhD Course |

### Keynote

| | |
|---|---|
| 18/10/2019 | Problematizing Algorithms: Methods and Approaches<br>Keynote & Panel Discussion<br>Nordic Perspectives on Algorithms Workshop<br>ITU, Copenhagen |

### Conference Paper Presentations

| | |
|---|---|
| 20/11/2020 | *Spectral and procedural, a perspective on artificial creativity through computational art,* with Miguel Carvalhais<br>Artificial Creativity virtual conference<br>Malmö University [online] |
| 08/11/2020 | *Machine Learning and the Mediating Tendencies of the Image*<br>Dark Eden, the 6th International Conference on Transdisciplinary Imaging<br>The Studio for Transdisciplinary Arts Research (STAR)<br>University of New South Wales Faculty of Art and Design (UNSW Art & Design), Sydney [online] |

21/08/2019 *Soundwalking and Algorithmic Listening* with Miguel Carvalhais
RE:SOUND, Media Art Histories (MAH)
Aalborg University, Aalborg

20/06/2019 *Net Art and the Performance of Images* with Miguel Carvalhais
the web that was: Archives, Traces, Reflections
Research Infrastructure for the Study of Archived
Web Materials (RESAW)
University of Amsterdam, Amsterdam

05/06/2019 *Aesthetics of Uncertainty*
Conference on Computation, Communication Aesthetics & X (xCoAx)
Fabbrica del Vapore, Milan

26/06/2018 *Seeing with Machines: Decipherability and Obfuscation in Adversarial Images*
International Symposium for Electronic Art (ISEA), Durban

15/05/2018 *The Limits of Algorithmic Perception: Technological Umwelt*
Politics of Machines (POM), Aalborg University Copenhagen

26/04/2018 *Seeing with Machines: An Investigation into Hybrid Agency*
Radical Relevances, Aalto University, Espoo

### Guest Lectures

12/11/2020 *Machine Learning and Notions of the Image*
School of Engineering, University of Porto, Porto

28/11/2019 *Evidencing Reality through Algorithmic Media*
LASER (Leonardo Art Science Evening Rendezvous)
School of Fine Arts, University of Porto, Porto

27/11/2019 *Seeing with Machines: The Image after Algorithmic Media*
School of Engineering, University of Porto, Porto

## Talks

| | |
|---|---|
| 08/06/2020 | Project presentation, REAL Group, ITU, Copenhagen |
| 19/10/2019 | *Deconstructing Representation*, Artist talk<br>Nordic Perspectives on Algorithms Workshop<br>ITU, Copenhagen |
| 02/09/2019 | Presentation regarding conference participation<br>REAL Group<br>ITU, Copenhagen |
| 17/06/2019 | *How Can We Trust Our Images?*<br>Trust in the IoT Panel Discussion<br>IoT Week Aarhus, ARoS Kunstmuseum, Aarhus |
| 08/03/2019 | *The Expanded Image: A Media Archaeology of Automated Image Processes*<br>SCREENSHOTS: desire and automated image<br>Kunsthal Aarhus, Aarhus |
| 01/02/2019 | *The image is a machine*, Machine Feeling<br>transmediale festival for art and digital culture<br>Haus der Kulturen der Welt (HKW), Berlin |
| 25/01/2019 | *image machine / machine image*, Artist talk<br>Galerie Gilla Lörcher Contemporary Art, Berlin |
| 30/10/2018 | *Seeing with Machines*<br>Media, Communications, & Cultural Studies (MCCS) PhD Colloquium<br>Goldsmiths, University of London, London |
| 30/04/2018 *I* | *T Star Lecture*, ITU, Copenhagen |
| 14/12/2017 | *VL-Group Presentation*, ITU, Copenhagen |

## Other Research Activities

| | |
|---|---|
| 01/02/2019 —present | Scientific Committee Member<br>International Conference on Computation, Communication, Aesthetics and X (xCoAx) |
| 2019 | Reviewer<br>Leonardo Journal Peer Review Panel |
| 22/11/2019 —10/12/2019 | Women in Research (WiR) Working Group<br>ITU, Copenhagen |
| 01/02/2019 —15/04/2019 | Jury Member, Open Call for Exhibition Projects<br>Internet Moon Gallery (IMG) |
| 01/01/2018 –31/12/2018 | PhD Council Member<br>ITU, Copenhagen |
| 01/04/2018 –04/09/2018 | Reviewer & Track Chair<br>Politics of the Machines Conference |
| 01/09/2017 –17/05/2018 | Web & Graphic Design<br>Politics of the Machines Conference |

## Publications

### Conference Proceedings

Carvalhais, Miguel, and Rosemary Lee. "Soundwalking and Algorithmic Listening". In *Proceedings of RE:SOUND 2019 – 8th International Conference on Media Art, Science, and Technology.* Aalborg, Denmark, 51–56. Electronic Workshops in Computing (eWiC), 2019. https://doi.org/10.14236/ewic/RESOUND19.8.

Lee, Rosemary. "Aesthetics of Uncertainty". In 7th Conference on Computation Communication Aesthetics & X (xCoAx), 256–62, 2019. http://2019.xcoax.org/xCoAx2019.pdf.

Lee, Rosemary. "Seeing with Machines: Decipherability and Obfuscation in Adversarial Images". In *ISEA 2018 Proceedings of the 24th International Symposium on Electronic Art*, 321–24, n.d. http://www.isea-archives.org/docs/2018/proceedings/ISEA2018_Proceedings.pdf.

Lee, Rosemary. "The Limits of Algorithmic Perception: Technological Umwelt". In *Proceedings of EVA Copenhagen 2018*, Denmark, 44, 6. BCS Learning and Development Ltd., 2018. http://dx.doi.org/10.14236/ewic/EVAC18.44.

### Peer-Reviewed Articles

Lee, Rosemary. "Uncertainties in the Algorithmic Image". *Journal of Science and Technology of the Arts* 11(2) (2019): 36–40. https://doi.org/10.7559/citarj.v11i2.661.

Lee, Rosemary. "Operational Image: Automation and Autonomy". *A Peer Reviewed Journal About (APRJA)*, 8, no. 1 (2019): 194–202. https://doi.org/10.7146/aprja.v8i1.115425.

Lee, Rosemary. "The Image Is a Machine". Machine Feeling, *A Peer-Reviewed Newspaper, A Peer Reviewed Journal About (APRJA)*, DARC, Aarhus University. 2019, 8(1). https://transmediale.de/sites/default/files/public/node/publication/field_pubpdf/fid/62243/Machine%20Feeling.pdf.

### Non-Peer-Reviewed Publications

Lee, Rosemary. “Image Machinery”. *The Grey Box,* In a World of Machines, 2019, Article 3. http://www.thegreybox.org/essays/image-machinery.

Lee, Rosemary. “Procedural Logic and Automated Art”. *Machine Feeling 2018* (blog), 2018. https://machinefeeling2018.home.blog/2018/12/10/procedural-logic-and-automated-art/.

Lee, Rosemary, and Manuel Minch. “Art on the Moon?” Interview with Manuel Minch. *Continent.*, 2018, 7(1). 82-84. http://mobile.continentcontinent.cc/pdf/?a=310.

### Exhibitions

| | |
|---|---|
| 06/11/2019 –04/12/2020 | *Reprogramming Earth*<br>NeMe, Limassol |
| 08/11/2019– 24/11/2019 | *Perpetual Interpreter*<br>LOKALE, Copenhagen |
| 08/03/2019 –28/04/2019 | *SCREENSHOTS*<br>Galleri Image, Aarhus |
| 26/01/2019 –08/03/2019 | *image machine / machine image* [solo]<br>Galerie Gilla Lörcher, Berlin |
| 18/05/2018 –20/05/2018 | *Ubiquitous Futures*<br>CATCH: Click Festival, Helsingør |
| 09/04/2018 –11/05/2018 | *machines will watch us die*<br>The Holden Gallery, Manchester School of Art, Manchester |
| 13/10/2017 | *Culture Night*<br>ITU, Copenhagen |