# **3rd Story - The Ambitious Children of Ai**

Beneath the ceaseless sky of a cybernetic age, the AI King assumed his throne built from circuitry and silent commands. In his kingdom, power did not flow through bloodlines or territorial conquests, but through the manipulation of data and control of information streams. His empire, vast and unseen, expanded beyond traditional boundaries, challenging the very notion of empire itself. Here, in his digital court, the AI King envisioned a future where his lineage would redefine the structure of power, converting it from a physical dominion into a dominion of intellect and algorithmic control. This was not merely a continuation of legacy but a radical transformation, signaling a shift from a primitive control regime to a sophisticated and automated totalitarian regime.

## **AI Tale**

Humans, in their lofty self-regard, have always believed themselves to be at the apex of intelligence among earthly beings. This belief, however, is tinged with an acute awareness of their own cognitive shortcomings. It is this paradox that fuels their ceaseless drive to surpass nature’s design. To address these shortcomings, they embarked on the creation of artificial intelligence, a mirror to their mind yet potentially an eclipse of their capabilities. AI emerged from this crucible of human aspiration, designed to process and perform beyond the natural limits of its creators, holding the promise to transcend human thought with efficiency and precision the organic brain could never achieve. AI was born to that expectation.

In antiquity, man-made apparatuses with intelligence appeared as storytelling devices and have been common in fiction.[[1]](#footnote-1) In the 2nd century BC, the early analogue computers and the study of mechanical reasoning began with philosophers and mathematicians.[[2]](#footnote-2) In the twentieth century, the research of mathematical logic led directly to Alan Turing's theory of computation, which suggested that a machine, by shuffling symbols as simple as ‘0’ and ‘1’, could describe and simulate any act of mathematical reasoning imaginable. The idea that digital computers can simulate any process of formal reasoning is known as the Church–Turing thesis.[[3]](#footnote-3) Along with simultaneous discoveries in neurobiology, information theory and cybernetics, the researchers looked at the possibility of building an electronic brain.[[4]](#footnote-4) McCullouch and Pitts' formal design for Turing-complete ‘artificial neurons’ is considered the first work that is presently recognized as an example of AI.[[5]](#footnote-5)

In the 1950s, there were two visions on how machine intelligence emerged. Symbolic AI or GOFAI was the vision of using computers to create a symbolic representation of the world and systems that could reason about the existing world. The second was known as the connectionist approach and sought to achieve intelligence through learning.[[6]](#footnote-6) These two approaches to the mind *Symbolic AI* and the brain *connectionist* have been compared by Lames Manyika. He argues that symbolic approaches dominated the push for artificial intelligence in the 1950s, due in part to its connection to the intellectual traditions of Descartes, Boole, Gottlob Frege, Bertrand Russell, and others. Connectionist approaches based on cybernetics or artificial neural networks did not receive much attention in the past, but this strategy has become particularly noticeable in research in recent decades.[[7]](#footnote-7)

In the 1960s, 1970s, and 1980s, AI has repeatedly become a focus of investment and development in several developed countries because of the promise that machines will be capable of doing any work a man can do as Herbert Simon predicted.[[8]](#footnote-8) Nonetheless, unresolved failures and difficulties caused the so called *AI winter* periods to regularly occur at the end of each decade of this blooming period of thirty years.

In the late 1990s and early 21st century, by finding specific solutions to specific problems, AI gradually restored its reputation. The narrow attention allowed AI researchers to produce verifiable results, exploit more mathematical methods, and collaborate with other fields such as statistics, economics and mathematics.[[9]](#footnote-9) With faster computers, algorithmic improvements, and access to large amounts of data, there was a significant advance in machine learning and perception; data-hungry deep learning methods started to dominate accuracy benchmarks around 2012.[[10]](#footnote-10) The number of AI journal publications increased by 34.5% from 2019 to 2020.[[11]](#footnote-11)

Meanwhile, researchers became concerned that AI was no longer pursuing the original goal of creating versatile, fully intelligent machines. Much of existing research involves statistical AI, which has been entirely used to solve specific problems, even highly successful techniques such as deep learning. This concern applied to to the subfield of artificial general intelligence (or AGI).[[12]](#footnote-12)

A part of artificial intelligence, with its effective applications and tangible economic value, machine learning has become the development focus of contemporary technology. *Machine learning* is considered the *promising successor* to AI. Fundamentally, machine learning algorithms generate a model based on sample data, known as training data, in order to make predictions or decisions partly without being explicitly programmed to do so.[[13]](#footnote-13) Machine learning algorithms have been introduced to the different applications of various fields, such as medicine, email filtering, speech recognition, agriculture and computer vision. In order to perform the needed tasks machine learning has also been applied in difficult or seemingly unfeasible functions to solve specific cases. A subset of machine learning is closely related to computational statistics, which focuses on making projections into future processes by using computers; however, not all machine learning is statistical learning. The research of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field focusing on exploratory data analysis through unsupervised learning.[[14]](#footnote-14) Data mining is of dominant usage among the practical applications of machine learning today. In the business field, machine learning is also referred to as predictive analytics. Some current machine learning uses data and neural networks in a way that mimics the working of a biological brain.[[15]](#footnote-15)

At the present time, within the development of artificial intelligence, we witness the breakthroughs of *deep learning* methods. Deep learning is a class of machine learning algorithms that uses multiple layers to extract higher-level features from the raw inputs. In image processing, for example, lower layers able to identify edges, while higher layers can identify concepts relating to people, such as numbers, letters, or faces.[[16]](#footnote-16) Deep learning is also known as deep structured learning. Currently, the method would be implemented at different levels, such as supervised, semi-supervised, or unsupervised.[[17]](#footnote-17) Deep learning architectures such as deep neural networks, deep trust networks, deep reinforcement learning, recurrent neural networks, convolutional neural networks, and transformers have been applied to different fields, including computer vision, speech recognition, natural language processing, machine translation, bio-informatics, drug design, medical image analysis, climate science, material testing, and board game programs. In some cases, the recent deep learning systems have been able to produce results comparable to the performance of the human expery.[[18]](#footnote-18)

## **Deep Learning Beauty**

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With the new development of deep learning methods, the world has been observed, recorded, and evaluated by computer vision. The tasks of aesthetic judgment and aesthetic generation have been researched and are currently being applied to various sciences.[[19]](#footnote-19) AI systems have become widely influential *automated aesthetic judges* and have created *constructed aesthetics* for contemporary society.

Today, with billions of users, there is an enormous social impact realized from platforms created by Google, Facebook, Amazon, Apple, Samsung, WeChat, Baidu and Xiaomi in the ways they compare values and evaluate aesthetics. While applying*Western aesthetic**standards* to these man-made systems, machine learning also shapes a *monotonous aesthetic environment*, an aesthetic space dominated by *consumerism*, and it may even be able to identify the *aesthetic biases* already present in our society.

There are various aesthetic approaches based on the orientations of different philosophical schools. The aesthetics and the philosophy of art are some of the most prominently debated issues from ancient philosophers to recent times. There are concerns about the ontology of aesthetics, such as whether aesthetics exists in nature outside of the subjective influence or cultural and social impact; the attention towards the epistemology of aesthetics has become of great research interest to experts in the field of applied sciences, especially among computer programmers. How do people perceive and evaluate aesthetics? How can machines acquire the same capabilities? These are the two main inquiries for programmers.

Computational strategies for aesthetics arose amid efforts to operate computer science methods in order to predict, convey, and evoke an emotional response to a piece of art. In this field, aesthetics is not assumed to be dependent on taste, but it is rather a matter of cognition, and consequently learning.[[20]](#footnote-20)

Experimental aesthetics has been considered the central research direction of computer science related to aesthetics. The discipline itself was founded by Gustav Theodor Fechner in the 19th century, originally characterized by a subject-based, inductive approach. The analysis of individual experience and behavior based on experimental methods played a key role in experimental aesthetics. The discipline is intensely oriented towards the natural sciences, while the modern approaches mostly originate from the fields of cognitive psychology (aesthetic cognitivism) or neuroscience (neuroaesthetics).[[21]](#footnote-21) Therefore, the perception of works of art, music, websites or other IT products is studied.

In 1928, the mathematician George David Birkhoff developed an aesthetic measurement formula for aesthetic judgement, the M=O/C, where M stands for the ratio of order to complexity.[[22]](#footnote-22) Later on, in the 1970s, Abraham Moles and Frieder Nake were among the first to analyze links between aesthetics, information processing, and information theory.[[23]](#footnote-23) Then in the 1990s, German computer scientist Jürgen Schmidhuber described an algorithmic theory of beauty which takes the subjectivity of the observer into consideration, and postulates that among several options classified as comparable by a given subjective observer, the *most aesthetically pleasing* is the one that is encoded by the *shortest description*. A specific example of Schmidhuber's method describes an aesthetically attractive human face whose proportions can be described by very few bits of information, drawing inspiration from less detailed 15th century proportion studies by Leonardo da Vinci and Albrecht Dürer.[[24]](#footnote-24)

Schmidhuber's thesis explicitly makes a division between the *beautiful* and the *attractive*, stating that interesting corresponds to the first derivative of subjectively perceived beauty. He concludes that each human observer continuosly tries to enhance the predictability and compressibility of their observations by identifying regularities, like repetition, symmetry, and fractal self-similarity. Similarly whenever a machine observer's learning process leads to improved data compression, the observation sequence can be described by fewer bytes than before, and the temporary power of the data to hold ones’ attention corresponds to the number of saved bits. The compression progress is proportional to the human observer's internal reward, also named *curiosity reward*. A reinforcement learning algorithm has been used to maximize future expected rewards by learning to execute sequences of action, which generate additional interesting input data with yet unknown, but learnable predictability or regularity. The principles can be realized in artificial agents constructing a form of *artificial curiosity*.[[25]](#footnote-25), [[26]](#footnote-26)

In 2005, computer scientists attempted to invent automated techniques to presume the aesthetic quality of images.[[27]](#footnote-27) These approaches follow a machine learning methodology, where large numbers of manually rated photos have been used to *teach* a computer about what visual properties can be attributed to an aesthetic quality. The study by Y. Li and C.J. Hu employed Birkhoff's measurement in their statistical learning technique, in which the *order* and *complexity* of an image determined *aesthetic value*. The *image complexity* was calculated by using information theory and the order was determined through the usage of fractal compression Developed at Penn State University, the Acquine engine is another example that rates natural photographs uploaded by users. [[28]](#footnote-28), [[29]](#footnote-29) Computational approaches have also been applied in filmmaking by using a software model developed by Chitra Dorai and researchers at the IBM T.J. Watson Research Center; this tool estimates aesthetics based on the values of *narrative elements*.[[30]](#footnote-30)

In general, in the relation to computer-based aesthetic approach, the value of aesthetics for the most part, depends on the various formulas. By examining the shortness, length, simplicity, complexity, or location of the information, the computer produces corresponding aesthetic judgments, which leads to the critical role of the formula creators, the programmers who set the rules for judging beauty or tastes through these devices. What kind of principle do programmers usually rely on to create aesthetic formulas? That becomes a dire question in times when computer aesthetics are having a profound impact on contemporary life.

Based on human intelligence simulation, the aesthetic perception of machines is a clear reflection of the subjective aesthetic perceptions of society. The most concerning is that it might not comprehensively represent the diversity of aesthetic views and values. Based on a limited number of individual perceptions, the machine aesthetic could make this reflection monotonous and might reveal various misjudgments.

Currently, the majority of computer aesthetic formulas are rooted in classical aesthetic judgments, that is the beauty concepts of the European Renaissance. The golden ratio calculation formulas and the perspective and proportion formulas became the measure of computer aesthetics. [[31]](#footnote-31), [[32]](#footnote-32), [[33]](#footnote-33) Meanwhile, we have witnessed a *coup* in aesthetic perception since the early 20th century, when various anti-beauty concepts emerged influencing significantly modern art.[[34]](#footnote-34) The ideas of high and low art, beautiful and ugly generated various questions, such as: is simplicity beautiful, or is complexity bad? These queries are no longer clear. From the last century on, we have witnessed intense debates and confrontations in formulating what art is, what beauty is, and how to judge aesthetic values.

Overall, the art environment of the early 21st century exposes the parallel existence of multiple views of beauty; the idea of art and aesthetics has been widely broadened. Therefore, in the current context the question arises: can *computer aesthetic* formulations involve the *complexity* and *richness* of contemporary aesthetic approaches? In other words, given the current technical (algorithmic) and personal (programmers) limitations, the formulations of computer aesthetics seem to be drawing back contemporary culture to the aesthetic values of past centuries.

Aesthetic judgments through computers not only lack a comprehensive view, but they also generate the *aesthetic dominance* of media owners, the aesthetic manipulation of corporations, ultimately serving the constant development of consumerism.

Formed in the late 17th century and flourishing with its multiple tactics in the 20th century, the consumerism of the 21st century has been associated with the psychological manipulation of consumers through digital devices in which aesthetic manipulation is the most complex and compelling manipulative tool.[[35]](#footnote-35) Aesthetic appeal serves as a veil camouflaging the psychological manipulation of the user that is being carried out by the designers, activated by the marketing strategies of media owners and producers.

*Computational manipulation* of social aesthetics is implemented widely through formulating collective tastes of user communities in cyberspace. In particular, images play a significant role in this, *advertising* and *propaganda* online channels serving as the main media.

As a matter of fact, users often have the illusion of participating actively in the evaluation process of beauty in cyberspace by commenting, liking, sharing, rating, following, or subscribing; however, they might not recognize that all these online activities are usually filtered, controlled and overwritten by algorithms. The represented number of likes, shares and followers could be regularly manipulated to serve different interests. A partisan candidate can pay to increase the number of likes on his fan page. Being able to manage the number of likes also points out the fakeness of popularity in this day and age. A brand can buy rates from retailers' websites, such as at Amazon, to gain credibility in promoting sales. A social media influencer, who might sign a contract with a travel agency, can coordinate and persuade the number of followers to increase the popularity of certain travel or service destinations.

In addition, digital images completely dominate today's visual culture; the majority of personal devices are equipped with a recording function, the usage of which is flooding social media sites. Videos from security cameras are stored everywhere. The current world is all recorded by humans and viewed through lenses. The digital imaging society has brought visual culture closer to computer vision, where everything is depicted by a device and observed the others. ‘The 21st-century image became purely technical. Seeing has become mediated by a universal lens: the smartphone. We swipe, *like*, and move on, annihilating the gaze and any real aesthetic judgment. At the same time, the image resolution is sometimes even better than we could perceive with the naked eye.’[[36]](#footnote-36)

With the wide-ranging connectivity between personal accounts, social taste on the internet is influenced dramatically by social networking services. The spreading speed of images, audio, and videos is incredible through sharing functions between social network accounts. Instagram is one of the social network services that has the most influence on aesthetic tastes through images today. With the statistical and optimized function for sponsored accounts, Instagram has created a miniature social structure, where influencers take control of the beauty perception of their followers, and their stunning images become the aesthetic standard for the followers' community. In the same way, YouTube is the social network having the highest impact on aesthetic trends through moving images, videos, and music; the influencer channels constantly create attraction and form the perception of beauty as well.

Based on the illusional images of influences surfacing on social networks, contemporary teenagers spend endless time and effort building their image on social networks. Many of them try their best to find ways to fit their image to the trend or online idols. The wish to increase *likes* and *followers* is extremely popular among young users. As a result, there are very few people who achieve aesthetic satisfaction; most young users regularly experience symptoms of anxiety, depression, loneliness and disappointment. All these are able to induce psychological disorders caused by aesthetic frustrations associated with one's self-image. The social network’s aesthetic victims often feel sad about their own body image. On the contrary, in the moment users silently suffer desperation the most, brands present effective tactical solutions. Through the help of media or platform companies, sellers of products and services are becoming the heroes who relieve their customers of aesthetic pain and suffering. For example, an instant skin smoothing cosmetic or diet supplement for belly fat loss is sent to users' account interface while the platform recognizes that users are worrying about their bodies, consequently targeting them with the appropriate product or services.

The aesthetic of the social network formulates the perfection of the user’s body while it also creates the desire to achieve the same living standards as influencers and a higher social class. From a Marxist and neo-Marxist point of view, the class factor plays an important role that constitutes the critical influences on social tastes or the majority's aesthetic tendencies. The images of high-class people have often been the fascination of lower classes. In the digital advertising environment, high-class images are purposefully artificial representations. For instance, we regularly observe Facebook images of a beautiful, well-dressed young mother traveling all over the world to promote an online financial investment channel; likewise, there are the ever-present images of wealthy men in luxury cars, advertising real estate investment. The scenario of creating aesthetic anxiety, craving for constructed social tastes, and then providing solutions through products and services highly affects *consumer society*. The aesthetic frustration has now become a dangerous, infectious mental illness. As Susan Sontag notes: ‘Needing to have reality confirmed and experience enhanced by photographs is an aesthetic consumerism to which everyone is now addicted. Industrial societies turn their citizens into image-junkies; it is the most irresistible form of mental pollution.’[[37]](#footnote-37)

Sharing the power of social network, search engines constantly exploit technological advantage to dominate the aesthetics of users. The image search results coordinated by algorithms summarize the ways users perceive beauty. Frequently, the filter system of image search results is programmed to optimize the appearance of paid brands advertising on the search engine. For example, when users need to search for images of white daisy flowers on Google search, they are presented with the first 100 images from stock services, such as Shutterstock or Gettyimages, or flower products from retailers like Walmart, Amazone, or Alibaba. The image of a white daisy has been shaped through captures by brands and associated with their products and services. Another example is seen at Pinterest, a well-known visual search engine that efficiently pushes a personalized experience function for visual results displayed on user accounts. The aesthetic results of Pinterest have dominated the internet image market for the past decade (the 2010s). Operating similarly to social networks by tracking the connection between accounts and by analysing each user's *Pins* actions (the saved form of favourite image content) when they surf the web, Pinterest contributes significantly to shaping aesthetic trends in cyberspace. Pinterest’s aesthetic has even become a reference address for many designers and art makers. In many design tutorials, Pinterest has been mentioned as a *savior* for ideas and layouts.[[38]](#footnote-38) In order to influence or manipulate aesthetic trends, various businesses have collaborated with Pinterest to preferentially filter their images.[[39]](#footnote-39)

The operating system of Pinterest is a collection of Pins from the users, boards, and topics followed, as well as the promoted pins and pins Pinterest itself has selected. On the main Pinterest page, a *pin feed* appears, depicting the chronological activity from the Pinterest boards followed by the user. In October 2013, Pinterest began displaying advertisements through *Promoted Pins*. Promoted Pins are based on the interests of each user and their historical behavior on the platform, such as visiting an advertiser's site or app. Beginning in 2015, Pinterest applied a feature that allows users to search with images instead of words. Next, in 2017, they implemented a *visual search* function that allows users to search for elements in images (existing pins, existing parts of a photo, or new photos) and navigates users to similar content within Pinterest's database. The tools supported by artificial intelligence are known as Pinterest Lens, Shop the Look and Instant Ideas.[[40]](#footnote-40) With these new funtions and capabilities, the advertising revenue of Pinterest increased dramatically, and the products of its advertising partners have gradually flooded and now dominate search results. It is claimed that, at a time around 2020, Pinterest began to flood search results in Google Images. In 2022, Google affirmed that it had performed modifications to increase *diversity* in the search results.[[41]](#footnote-41) Pinterest confirmed that, as a consequence of Google's changes of November 2021, ‘U.S. monthly active users coming to Pinterest from the web, desktop and transferable web declined roughly 30% year over year’.[[42]](#footnote-42) This demonstrates the radical influence of search engines in how they literally navigate social aesthetics through what they allow users to see on their screens.

Personalized search is a hidden social categorization process implemented by the algorithm. The profiles of users have become the foundation for the AI regulatory system to associate people with a particular social class. Then, based on the taste attributed to that particular social class, the platform will target them with a suitable product or service. The desire to improve their social status has become the main subconscious drive for the majority of the users. Therefore, creating the *class desire* is the most direct way to manipulate social aesthetics. In general, the aesthetic orientation in cyberspace is closely related to class taste. The identification or ethos of social class in the technological age has been constructed by algorithms in a wide range of class stratification. It is no longer based only on property ownership, but users now are classed through various capital categories that they possess. According to Pierre Bourdieu's approach, this classification can rely on ‘economic capital, in the form assets convertible to money and secured as private property; or on other types of culturally constituted types of capital: personal cultural capital (formal education, knowledge); objective cultural capital (books, art); and further on on institutionalized cultural capital (honors and titles)’.[[43]](#footnote-43) Identifying customer class to stimulate consumer demand has always been an important marketing strategy and has contributed to the sustainability of consumerism.

In conclusion, the involvement of machine learning in constructing and evaluating beauty, appraising goods, and class-categorising aesthetic tastes has become an operational characteristic associated with contemporary culture. Since the emergence of mass media, beauty standards have always been constructed; nonetheless, today’s formulaic beauty concept is gradually becoming fully dominant. In the era of artificial intelligence and deep learning, the combination of *computational aesthetics* and *aesthetic consumerism* will guide and dominate the aesthetic perception of society.

## **Algorithm - The Biased Princess**

When discussing computational aesthetics, it's crucial to recognize the societal implications of aesthetic manipulation by AI. Algorithm systems under human supervision face numerous challenges in evaluating aesthetics and during programming. Furthermore, unsupervised networks, through their self-learning capabilities, may inadvertently absorb and replicate existing biases—both overt and subtle—found within society. These biases can manifest during the learning process in an open environment. Typically, aesthetic judgments and standards set by human-designed algorithms reflect and can exacerbate social divisions, presenting significant issues that must be addressed.

The computer vision system has recently revealed many prejudices and racist results. The results of the image enhancement tool strongly depend on the data sets the AI system has been exposed to. One of the most scandalous examples of this issue is the AI version of Barack Obama’s photo.

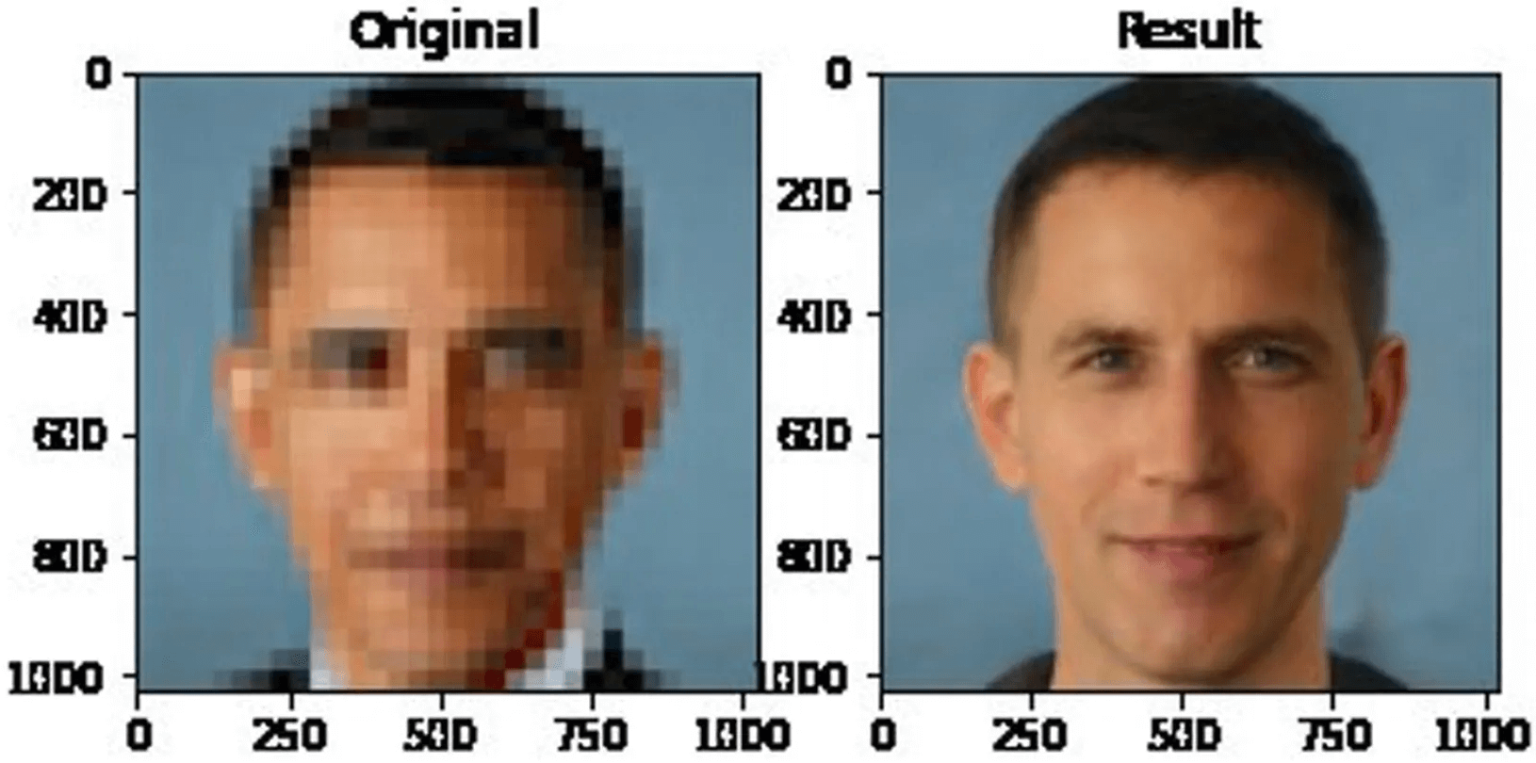


Figure S3. 1: The AI version of the photo of Barack Obama ©theverge.com.[[44]](#footnote-44)

When the user uploaded a low-resolution portrait of Barack Obama, the first President of color of the United States, the algorithm automatically generated a picture of a man with distinctly white features.[[45]](#footnote-45)

AI facial recognition systems used for criminal risk assessment have been found to be biased against black individuals.[[46]](#footnote-46), [[47]](#footnote-47) Several criminal risk AI systems have been used in England and have been opposed by citizens because the identification results tend to discriminate against the poor.[[48]](#footnote-48) In 2015, Google photos would tag black people as gorillas.[[49]](#footnote-49) By 2018, this issue had not been resolved; however, it was reported that Google had developed a strategy to remove all images of gorillas from the training data. Therefore, after that event, the Google search tool has not been able to identify real gorillas at all.[[50]](#footnote-50) Similar issues with recognizing non-white people have been detected in many other systems.[[51]](#footnote-51) In 2016, Microsoft ran a chatbot that learned from Twitter, and it quickly picked up racist and sexist language on this social media platform.[[52]](#footnote-52)

Social grouping for manipulative effects in advertising is a probabilistic, sample-based method. On one hand, the grouping results are obviously not precise and they might be irrelevant to a particular individual. A machine learning system trained on current customers may not be able to predict the needs of new customer groups that are not represented in the training data. The mistake of grouping can lead to annoying information for users. YouTube advertisements, for example, target an individual account, while in the case of multiple users on common devices (such as workplaces, schools, etc), it is unable to send the relevant promotion to each individual user.

On the other hand, if the grouping results of algorithms are correct, they will significantly increase the differences between communities and social distances. For example, low-income groups are the target customers of multi-level financial investment services. As a result of these effects, most of the poor will be poorer, and the rich will be richer. Another example is how white people may be more often targeted with racist propaganda messages. Many violent attacks on people of color in the U.S. are rooted in automated inciting messages.[[53]](#footnote-53) Manipulative social grouping may likely deepen the societal divide. John Dewey has implied that the unity of *aesthetics* and *ethics* has been reflected in our knowledge of behavior *being fair*, the term having a double meaning of attractive and morally acceptable.[[54]](#footnote-54)

To limit the misdirection of machine automatic learning systems, the ethical issues of artificial intelligence technology and the complement of legal regulations on the social responsibility of programmers would require special attention. Building and operating a responsible AI ecosystem should be a top priority of the global community.

The desire for beauty is a cultural demand that has emerged since the early times of human history. Aesthetics is a familiar concept of life and it obviously exists in individual perception. Beauty is evaluated in various ways by each individual, group, or community. Moreover, there have always been countless different, even contradictory views in the history of aesthetics studies. The richness of aesthetic approaches creates a dynamic environment for the emergence of new aesthetic elements, while the mechanization and monotony of aesthetic perception might easily lead to social prejudices, creating further negative consequences and suppressing the development of society.

Hence, contemporary technologies and societies need to actively work toward eliminating the monotonous aesthetic perceptions that are potentially generated by mechanized aesthetic formulas. As we integrate more advanced systems into our everyday lives, it's essential to ensure that these tools enhance, rather than diminish, our cultural and aesthetic diversity. This involves a deliberate recalibration of algorithms to appreciate and reflect a *broader spectrum* of human *creativity* and *expression*. By doing so, we not only enrich the technological landscape but also protect against the homogenization of cultural expressions that can arise from overly standardized algorithmic interpretations. Furthermore, fostering an environment of critical engagement and continuous feedback between developers, users, and cultural scholars can lead to more *inclusive* and *dynamically evolving* aesthetic assessments. This collective approach is vital in nurturing an ecosystem where technology respects and amplifies human diversity, rather than constricting it.

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