Literature Review

Contents

[1. Overview 3](#_Toc122701630)

[2. Artificial Intelligence(AI) 3](#_Toc122701631)

[3. Neural Networks(NNs) 5](#_Toc122701632)

[4. Deep Learning 9](#_Toc122701633)

[5. Generative Adversarial Networks(GANs) 9](#_Toc122701634)

[6. Artwork Creations using AI 12](#_Toc122701635)

[7. Deep Learning 15](#_Toc122701636)

[8. References 19](#_Toc122701637)

Figures

[Figure 1 An example of a neural network 6](#_Toc122701668)

[Figure 2 Timeline of architecture-variant GANs 10](#_Toc122701669)

[Figure 3 an excellent single-image resolution that shows results of the benefit of using a Gan model trained to generate realistic sample from a multimodal distripution 14](#_Toc122701670)

## Overview

Generative Adversarial Networks (GANs) were first proposed by Ian Goodfellow in 2014 as a novel approach to generate synthetic images using Deep Learning. The approach proposed in his paper suggests using a generator and a discriminator. Both generator and discriminator are deep Neural Networks. The generator takes as input a set of random numbers from a Gaussian space and will output a fake image synthesizing the training data. The discriminator will take as input an image and then output a probability of whether the image is real or fake. By using the gradient descent and a custom loss function, the generator model will be able to learn how to fool the discriminator. In the original paper, both generator and discriminator consisted of deep multi-layer perceptron. This revolutionary idea opened a wide scope of applications in AI including computer vision (Gintare et al., 2015), Natural Language Processing (Dai et al.,2017) and semantic segmentation (Pauline et al, 2016). Having that said, studies on the use of GANs for generating fine artwork is lacking in the literature (Tumei et al., 2019). Therefore, I have decided to conduct a study on the effect of GANs for generating fine artwork.

## Artificial Intelligence(AI)

The science and engineering of creating intelligent machines, particularly intelligent computer programs, is known as artificial intelligence. Although it is related to the related job of utilizing computers to comprehend human intelligence, AI should not be limited to techniques that can be observed biologically. People, many animals, and some machines all exhibit intelligence in various forms and to varying degrees(McCarthy 2004). An important technology that underpins routine economic and social activity which is the AI. In addition to resolving a number of social issues, it makes a significant contribution to the economy of Japan's sustainable growth. In wealthy nations like Europe and the United States and developing nations like China and India, it has gained prominence as a key to progress in recent years. New robot technology(RT) and artificial intelligence-based information and communication technologies (ICT) have received the majority of the attention. Despite the fact that freshly created AI technology excels at extracting particular patterns, there are significant restrictions (Lu et al. 2017). Philosophy, logic, biology, psychology, statistics, and engineering all include plenty of hints about what could be required to make robots intelligent. People began to use the hints from these areas in their individual efforts to automate various components of intelligence with a constantly increasing intensity. Despite the fact that people have been using logic for thousands of years, the Greek philosopher Aristotle was the first to attempt to study and codify the process.

When some facts are said, something else must necessarily follow from the fact that they are stated, according to Aristotle's definition of the syllogism(J.Nilson 2009).

Businesses would benefit from considering AI from the perspective of business capabilities rather than technologies. In general, AI can assist three crucial business requirements: automating company activities, learning from data analysis, and interacting with clients and staff. (See "Cognitive Projects by Type" exhibit.) automation of processes. The majority of the 152 projects we looked at included employing robotic process automation(RPA) technologies to automate physical and digital tasks—typically back-office administrative and financial functions. RPA is more sophisticated than prior business-process automation solutions because the "robots" (which are actually pieces of server-side code) behave like humans while entering and consuming data from various IT systems(Davenport et al. 2018). Since then, numerous academic disciplines have contributed to its research. Computer scientists have created sophisticated deep learning algorithms (LeCun, Bengio, & Hinton, 2015), while scholars in business management have examined the effects of AI on customers, businesses, and stakeholders in an increasingly automated and interconnected corporate world (Cath, 2018). (Huang & Rust, 2018). However, these developments in AI research have mostly been carried out in closed-off silos with little cross-disciplinary collaboration. Similarly, it has been challenging to come up with a singular, widely accepted its definition(Loureiro and Tussyadiah2021).

## Neural Networks(NNs)

A highly stylized illustration of a neuron, which makes up an estimated 10 11 (100 billion) in the human brain, is illustrated in Figure 1.1. Electrical signals, which are brief impulses or "spikes" in the voltage of the cell wall or membrane, are used by neurons to communicate. Electrochemical junctions called synapses, which are found on cell branches known as dendrites, mediate the interneuron connections. Each neuron typically has thousands of connections to other neurons, which results in an endless stream of incoming messages that eventually reach the cell body. Here, they are combined or integrated in some manner, and the neuron will "fire" or produce a voltage impulse in response if the resulting signal is greater than a predetermined threshold. The axon, a branching fiber, is then used to communicate this to other neurons(Gurney and York 1997).

Diagram

Description automatically generated

Figure An example of a neural network

An array of potent new methods for pattern recognition, data analysis, and control are made available by neural networks. High processing speeds and the capacity to learn a problem's solution from a series of instances are just two of their standout qualities. Studies of the mechanisms for information processing in biological nervous systems, particularly the human brain, served as the initial inspiration for neural networks. In fact, a large portion of current research on neural network algorithms is aimed at improving our comprehension of how biological systems process information. However, a completely abstract approach to information processing can also be used to comprehend the fundamental ideas. As a nonlinear mathematical function that converts a collection of input variables into a set of output variables, feedforward neural networks can be thought of as such. (Bishop, 1994). Deep neural networks have recently transformed a number of fields, including knowledge discovery, speech synthesis, picture recognition, and speech recognition (Krizhevsky et al.,2012; LeCun et al., 2012; Schmidhuber, 2015; LeCun et al., 2015; Van Den Oord et al.,2016). They are increasingly employed in real-world applications and crucial decision-making processes because of their superior performance and capacity to automatically learn from structured data. Examples include revolutionary knowledge finding techniques, autonomous driving, and medical image analysis. It is crucial that users can understand and evaluate these processes in order to take full advantage of their potential. For instance, it would be very helpful to know which characteristics aid a neural network in selecting suitable candidates in neural architecture (Zoph et al., 2018) or chemical compound searches (Montavon et al., 2013; Sch utt et al., 2017). Additionally, it might be a legal obligation for some applications to comprehend the decision-making process. Despite these considerations, neural networks are sometimes viewed as "black boxes" since it is unclear how they function inside or how they get their predictions(Alber et al.2019).

The weights of each unit must be changed in order to minimize the error between the planned output and the actual output when training a neural network to complete a task. The neural network must do this step by computing the weights' error derivative (EW). To put it another way, it must determine how the error alters as each weight is gradually increased or decreased. The backpropagation algorithm is the approach that is most frequently employed to calculate the EW(Hinton, 1992). In a variety of computer vision tasks, CNNs have produced state-of-the-art results, including object classification (Simonyan & Zisserman, 2014; He et al., 2016) and detection (Redmon et al., 2016; Ren et al., 2015), face recognition (Taigman et al., 2014), semantic segmentation (Long et al., 2015; Chen et al., 2018; Noh et (Cornia et al., 2018; Li et al., 2014; Jia & Bruce, 2019; Islam et al., 2018). However, in the context of deep learning, CNNs have come under fire for their lack of interpretability (Lipton, 2018). Capsule (Sabour et al., 2017) or recurrent networks (Visin et al., 2015) have been used to model relative spatial relationships within learned feature layers because the traditional CNN model is thought to be spatially-agnostic. Although absolute spatial information is crucial in position-dependent tasks, it is uncertain if CNNs can capture it (e.g. semantic segmentation and salient object detection). The areas judged to be the most salient (Jia & Bruce, 2018) frequently occur close to the center of an image. Even though the visual elements have not changed, the most salient region moves when saliency is detected on a cropped version of the photos. Given the constrained geographical scope of the CNN filters that are used to analyze the image, this is fairly unexpected. With the assumption that CNNs might indeed learn to encode position information as a signal for decision-making, the role of absolute position information has been investigated using a series of randomized tests. The findings show that the widely used padding procedure indirectly teaches position information (zero-padding). When applying convolution, zero-padding is frequently utilized to maintain the same dimensionality. Its unnoticed impact on representational learning has been ignored for a very long time. This study sheds light on an important finding and suggests a productive line of inquiry for the future while also advancing our understanding of the nature of CNNs' learnt properties. In earlier publications, learnt feature maps have been shown to help explain how CNNs operate. To create a pattern image that can optimize the activation of a particular unit, it is just a matter of computing losses and passing those backwards to the input space (Hinton et al., 2006; Erhan et al., 2009). However, as the number of layers increases, modeling such interactions becomes quite challenging. Zeiler and Fergus (2014) describe a non-parametric visualization method in recent work. In order to transfer learnt features back to the input space, a deconvolutional network is used (Zeiler et al., 2011). The researchers' findings show what kinds of patterns a feature map truly learns. To find the area that maximizes class-specific activation, Selvaraju et al. (2017) propose combining pixel-level gradients with weighted class activation mapping. An actual study (Zhang et al., 2016) has demonstrated that a basic network may achieve zero training loss on noisy labels as an alternative to visualization techniques. In conclusion, CNNs have developed as a solution to the impractical volume of weights associated with a fully connected end-to-end network. As a result, there is a trade-off in that only a portion of the image can be seen by kernels and their learnt weights. This seems to indicate approaches where networks rely more on cues like texture and color instead of shape (Baker et al., 2018). However, position data offers a strong hint as to where objects might appear in an image (e.g. birds in the sky) (Islam et al. 2020).

## Deep Learning

## Generative Adversarial Networks(GANs)

In the recent years, a great deal of research has been done on generative adversarial networks (GANs). The field of computer vision, where significant progress has been achieved in problems like plausible picture synthesis, image-to-image translation, facial attribute modification, and related domains, is perhaps where they have had the most important impact. The use of GANs to solve real-world issues still presents substantial obstacles, despite the notable results attained to date. In this article, we focus on three of those challenges. These are listed in the following: (1) the creation of high-quality photographs; (2) a variety in image creation; and (3) training that stabilizes photos. (Wang et al. 2021).

A rising number of people in the deep learning community are becoming interested in generative adversarial networks (GANs) (Goodfellow 2014). GANs have been used in a variety of fields, including semantic segmentation (Dong, 2017), time-series synthesis, computer vision (Prophy, 2019), natural language processing (Dai, 2017), and computer vision (Dziugaite, 2015). The generative model family in machine learning includes GANs. GANs are superior to other generative models, such as variational autoencoders, in that they can handle sharp estimated density functions, create desired samples quickly, remove deterministic bias, and work well with the intrinsic neural architecture (Goodfellow 2015). These characteristics have made GANs extremely successful, particularly in the area of computer vision, where they have been used for tasks including plausible picture synthesis (Choe 2017), image-to-image translation (Choi 2018), image super-resolution (Dong 2017), and image completion (Chen 2018).

Graphical user interface, application

Description automatically generated

Figure Timeline of architecture-variant GANs

Generative adversarial networks (GANs) have recently attracted the attention of artificial intelligence researchers. GANs are made up of a generator and a discriminator that were both trained using the adversarial learning concept and were inspired by two-player zero-sum games. GANs are used to create new samples by estimating the distribution that real data samples might have in the future. Due to the great potential for applications, such as image and vision computing, speech and language processing, etc., GANs have been extensively explored since their inception (K. Wang et al. 2017).

It has been stated in 2016 by the first developer of Gan Ian Goodfellow that It is reasonable to question the value of researching generative models, particularly those that can merely produce data rather than offering an approximation of the density function. Since the world already has an abundance of photographs, such models seem to simply provide additional images when applied to images. There are a number of reasons to study generative models, including the fact that training and sampling generative models is a great way to assess our proficiency with high-dimensional probability distributions. In a wide range of applied math and engineering areas, high-dimensional probability distributions are crucial elements. There are various ways that generative models can be utilized into reinforcement learning. Model-based and model-free reinforcement learning algorithms can be categorized, with model-based algorithms being those that include a generative model. To simulate potential futures, time-series data can be employed in generative models. These models could be applied in a variety of ways for planning and reinforcement learning. Given the current state of the world and fictitious actions an agent might take as input, a generative planning model can develop a conditional distribution over future world states. Generative models can make predictions on inputs with missing data and can be trained with missing data. Semi-supervised learning, in which the labels for many or perhaps most training samples are absent, is one particularly fascinating case of missing data. For modern deep learning algorithms to generalize effectively, they frequently need a huge number of labeled samples. One method for lowering the amount of labels is semi-supervised learning. Studying a large number of unlabeled cases, which are typically simpler to collect, will help the learning algorithm's generalization. Semi-supervised learning may be accomplished by generative models—and GANs in particular—fairly successfully. Machine learning can now work with multi-modal outputs thanks to generative models, particularly GANs. A single input may correspond to a number of distinct correct replies, all of which are valid solutions to multiple tasks.

It is not possible to train machine learning models that can provide numerous accurate responses using some conventional methods, such as minimizing the mean squared error between a desired output and the model's projected output. Predicting the next frame in a video is one instance of this situation. Last but not least, a crucial part of many operations is to provide realistic samples from a distribution such as Super-resolution of a single image: The objective of this challenge is to create a high-resolution equivalent from a low-resolution image. Because the model must provide more information to the image than was present in the input, generative modeling is necessary, tasks with the intention of producing art. The ability of generative models, and in particular, GANs, can be utilized to construct interactive applications that help users create realistic visuals that correlate to rough situations in their imaginations has been demonstrated in two recent studies and finally the applications for image-to-image translation can turn sketches into pictures or aerial photos into maps. There is a very long tail of inventive uses that are challenging to predict but valuable once they are found.

## Artwork Creations using AI

Even though a rich history would greatly benefit from approaches that can analyze and handle data from the creative realm, the applicability of computer vision to real paintings and artworks has rarely been examined. This is partly because there isn't nearly as much annotated creative data as there is in naturally occurring photo data. In order to bridge the gap between the visual characteristics of artistic and realistic data, it was presented as a semantic-aware framework that can translate artworks into photorealistic representations (Tomei et al. 2019).

The interest in artificial intelligence research has increased as a result of recent developments in machine learning (AI). This sparked debates about the limitations of machine intelligence, the potential threats, and social difficulties as well as the research of potential applications of AI in a variety of fields. The creation and interpretation of art may be the most elusive topic of interest in the investigation of the settings of the "human against AI" relationship. However, understanding and appreciating art are still thought to be uniquely human abilities. Many intriguing efforts are sprouting at the interface of AI and art. Large-scale digitization projects that were undertaken over the past few decades have significantly increased the number of art collections that are now accessible online. These art collections make it simple for us to browse and appreciate works of art that are housed in numerous museums and galleries throughout the globe. Large collections of digitized art images are now accessible, allowing us to not only visually examine various pieces of art but also to open up new interdisciplinary research options. Despite existing in separate material modalities, the real painting and its digital equivalent encode and communicate the same complex informational structure. Art historians can be quite interested in the contextual information that is frequently included in the characteristics of the canvas and paint, the information contained in a digital artwork's numerical representation also contains data for which the potential has not yet been fully realized. Building digital repositories to make it simpler to access and explore collections is typically the primary objective of digitization efforts. Despite the fact that many digitization efforts view this as their final product, it is crucial to stress that the presence of these collections is simply the first step and a crucial requirement for using cutting-edge computational techniques and opening up new research avenues. Computational techniques are typically employed to either adopt a distant seeing or a close reading approach in the context of analyzing digitized art(Lang, S 2018). Close reading refers to concentrating on certain elements of a single work of art or artistic output, typically addressing issues like computerized artist authentication and visual stylometry(Graham D.J. 2012). The majority of research on such subjects relies on the availability of fine-grained digital copies of the examined artworks and mostly focuses on brushstrokes and textural characteristics. One of the main issues in computational art analysis over the past ten years has been the automated classification of artworks based on characteristics like artist, style, or genre. The majority of past studies addressed the issue of automatically classifying artists, styles, and genres by extracting various manually created visual elements and using those attributes to implement various machine learning techniques. The introduction of Generative Adversarial Networks (GAN) dramatically increased the usage of AI in the production of visual art (Abadie, 2015). With the introduction of convolutional neural networks, significant progress has been achieved in improving classification accuracy (CNNs). Deep neural networks have also shown promise in examining the content of artworks and automatically identifying objects, faces, and other particular motifs in paintings, in addition to classification. In the year 2014 Crowley et al demonstrated that object classifiers trained using CNN features from natural images can successfully retrieve paintings including these items, which was one of the groundbreaking efforts in this field. Later research focused on the issue of retrieving paintings that portray a particular object as well as locating the object in the image and detecting content to find co-occurring patterns in collections. The use of deep learning models for various purposes necessitates the availability of large-scale, well-annotated datasets. Many museums and galleries have recently released digitized online copies of their collections (Cetinic and She, 2019).

A picture containing text, outdoor, different, line

Description automatically generated

Figure an excellent single-image resolution that shows results of the benefit of using a Gan model trained to generate realistic sample from a multimodal distripution

Scientists and artists have been experimenting with building computer algorithms that can produce art for the past 50 years. Some programs, like generative adversarial networks, were created for different purposes but are now used for creating art (GANs). As an alternative, software might be developed with the goal of producing creative results. Any form of art that requires programming to produce it is referred to as algorithmic art. The Merriam-Webster definition of art states that it is "the deliberate application of ability and imaginative creativity, particularly in the production of attractive things; the works so produced". This definition of art has evolved throughout the course of the 20th century to encompass works that are not always made as physical things and do not have an aesthetic objective (such as conceptual art) (performance art). The determination of the artist's intention, institutional display, and audience acceptance have all been crucial defining factors in the art world since the difficulties of Marcel Duchamp's approach (Mazzone and Elgammal, 2019).

Digital media art is a young field. Original works of art are frequently worth more than mere copies or digital files. Extremely efficient and simple to use, allowing for endless creative possibilities and additional exploration. Art is interpretive; it expresses what the creators normally believe and is made to appeal to the intelligence, feelings, and sensations of the viewer. Excellent art never ceases to astonish. Appealing imagery used in advertising can support a visual identity and influence consumer behavior. These have adapted electronic art to make it more available to artists and other creatives interested in exploring the possibilities of the medium. In the past, the only way for people to experience art was through looking at it with their eyes. However, thanks to the ongoing development of technology, people may now use virtual reality to experience aspects of art that they were previously unable to. Even more impressively, it creates a false impression of realism. Through various artificial intelligence technologies, new windows are opened for people to view the world, elevating the human experience to a new level (Juan Qian, 2022).

## Deep Learning

The majority of modern civilization is powered by machine learning, including social network content filtering, e-commerce website suggestions, and a growing number of consumer goods like cameras and smartphones. Machine learning algorithms are used to choose relevant search results, recognize things in images, convert speech to text, match news articles, messages, or products with users' interests, and identify objects in photographs. These applications are increasingly using a group of methods known as deep learning. Deep-learning techniques, which include several levels of representation, are generated by building straightforward but non-linear modules that each convert the representation at one level (which begin with the raw input) into a representation at a higher, marginally more abstract level. When enough of these changes are combined, extremely complicated functions can be learned. Higher layers of representation for classification problems accentuate characteristics of the input crucial for discrimination and decrease irrelevant variations. For instance, a picture is composed of a set of pixel values, and the learnt features in the first layer of representation often indicate whether or not there are edges present at specific angles and places in the image. Despite slight changes in the edge placements, the second layer often finds motifs by identifying specific combinations of edges. Following layers would identify objects as combinations of these pieces since the third layer may combine motifs into larger combinations that correspond to familiar object parts. The important feature of deep learning is that these layers of features are learned from data using a general-purpose learning technique rather than being created by human engineers. Deep learning is making significant strides in resolving issues that have long defied the best efforts of the artificial intelligence field. Due to its success in identifying complex structures in high-dimensional data, it can be used in a wide range of scientific, commercial, and governmental fields. Because deep learning requires relatively little manual engineering and can easily benefit from advances in the amount of compute and data available, we believe it will have many more breakthroughs in the near future. Deep neural network researchers are now working on new learning methods and designs, which will only hasten this development such as supervised learning, convolutional neural network and recurrent neural networks(LeCun et al. 2015).

Deep learning is a type of machine learning that gives computers the ability to interpret the world in terms of a hierarchy of concepts and learn from experience. There is no requirement for a human computer operator to expressly specify all of the knowledge required by the computer because the computer learns through experience. The concept hierarchy enables the computer to learn complex concepts by constructing them from smaller ones; a graph representing these hierarchies would have several levels. This book introduces a wide range of deep learning-related topics(Kim, 2019).

In many situations, deep learning techniques require optimization. For instance, we frequently use analytical solutions to optimization issues to demonstrate an algorithm's existence. An optimization problem can be used to model inference in a probabilistic model. The most challenging of all the deep learning-related optimization issues is neural network training. To address only one instance of the neural network training problem, it is not uncommon to spend days to months working on hundreds of machines. Due to the significance and cost of this issue, a unique set of optimization strategies have been created to address it. A gradient-decent method is one such method useful for optimizing deep neural networks(Bengio et al. 2015).

CNNs are similar to conventional Artificial Neural Networks(also known as ANNs and are computer processing systems that draw a lot of their inspiration on how organic nerve systems, like the human brain, function) in that they are made up of neurons that learn to optimize themselves (O'shea and Nash 2015). A type of feedforward neural network known as a convolutional neural network may extract features from data using convolutional structures. CNN does not require to manually extract features, in contrast to conventional feature extraction techniques. Activation functions imitate the function that only neural electric signals exceeding a specific threshold can be sent to the next neuron; CNN kernels represent numerous receptors that can respond to diverse aspects. People created loss functions and optimizers to train the entire CNN system to learn what we anticipated. CNN has various advantages over generic artificial neural networks, including local connectivity, weight sharing, and dimensionality reduction through down-sampling (Li and Yang 2021). Convolutional, pooling, and fully-connected layers are the three different types of layers that make up CNN. The convolutional layer's goal is to teach input feature representations. Several convolution kernels make up the convolution layer, which is utilized to compute various feature maps. Each neuron in a feature map is specifically linked to a region of nearby neurons in the preceding layer. The previous layer refers to this region as the neuron's receptive field (Gu et al. 2018).

## References

McCarthy, John. WHAT IS ARTIFICAL INTRODUCTION? 24 Nov. 2004, cse.unl.edu/~choueiry/S09-476-876/Documents/whatisai.pdf.

Gintare Karolina Dziugaite, Daniel M. Roy, and Zoubin Ghahramani. 2015. Training Generative Neural Networks via Maximum Mean Discrepancy Optimization. arXiv:1505.03906. Retrieved from <https://arxiv.org/abs/1505.03906>.

Tomei, M., Cornia, M., Baraldi, L., & Cucchiara, R. (2019). Art2real: Unfolding the reality of artworks via semantically-aware image-to-image translation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 5849-5859).

Lu, Huimin, et al. “Brain Intelligence: Go beyond Artificial Intelligence.” Mobile Networks and Applications, vol. 23, no. 2, 21 Sept. 2017, pp. 368–375, 10.1007/s11036-017-0932-8.

Zihang Dai, Zhilin Yang, Fan Yang, William W. Cohen, and Ruslan R. Salakhutdinov. 2017. Good semi-supervised learning that requires a bad GAN. In Advances in Neural Information Processing Systems. 6510–6520.

Pauline Luc, Camille Couprie, Soumith Chintala, and Jakob Verbeek. 2016. Semantic Segmentation Using Adversarial Networks. arXiv:1611.08408. Retrieved from https://arxiv.org/abs/1611.08408.

Davenport, Thomas, et al. Artifi Cial Intelligence for the Real World. 2018.

Gurney, Kevin, and New York. An Introduction to Neural Networks an Introduction to Neural Networks. 1997.

Luc, Pauline, et al. "Semantic segmentation using adversarial networks." arXiv preprint arXiv:1611.08408 (2016).

Bishop, Chris M. “Internet Archive: Scheduled Maintenance.” Web.archive.org, 1 Mar. 1994, web.archive.org/web/20060903153555id\_/www.stat.purdue.edu/~zdaye/Readings/Neural\_Networks\_and\_Their\_Applications.pdf.

Hinton, Geoffrey. How Neural Networks Learn from Experience. 1992, d1wqtxts1xzle7.cloudfront.net/51322826/scientificamerican0992-14420170112-9268-jkuw6i-with-cover-page-v2.pdf?Expires=1670208896&Signature=Qaf5Fthdh5vlq4vxD7bHaGZIdEWniFKFoodqNbyGKFFTojL3MVeasRX8UR9wOMbuFPcYbH3XgXnCzhUOZBHlv0yCey08uAc28hWh8YBLf63bGaqjl1Q13NRkiBGo2lUv4amUZgMJ7BlXXQ962GgvZHTv6dpEPhwFt50NYCt5jqIGdTdDiCLu4n0ZFbL5yuomW-BRCK0domP-PtNuBFERdHPZReTv~6wivakUCCFUE5V3Q6k5NHMr~DyWO46QyLVKWsaL2ISuSa8tXhDr9sDN0uLVG7v9kTmil-2Ktu9aQRJRfFOmAb-LFtn3oYxgtgMDBtpBdgJIRGxYI2aYNy~woA\_\_&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA.

Wang, Zhengwei, et al. “Generative Adversarial Networks in Computer Vision.” ACM Computing Surveys, vol. 54, no. 2, Apr. 2021, pp. 1–38, 10.1145/3439723.

Wang, Kunfeng, et al. “Generative Adversarial Networks: Introduction and Outlook.” IEEE/CAA Journal of Automatica Sinica, vol. 4, no. 4, 2017, pp. 588–598, ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8039016, 10.1109/JAS.2017.7510583.

Tomei, Matteo, et al. Art2Real: Unfolding the Reality of Artworks via Semantically-Aware Image-To-Image Translation. 2019.

Cetinic, Eva, and James She. UNDERSTANDING and CREATING ART with AI: REVIEW and OUTLOOK a PREPRINT. 2021.

Mazzone, Marian, and Ahmed Elgammal. “Art, Creativity, and the Potential of Artificial Intelligence.” Arts, vol. 8, no. 1, 21 Feb. 2019, p. 26, 10.3390/arts8010026.

Juan Qian, Juan Qian. “Research on Artificial Intelligence Technology of Virtual Reality Teaching Method in Digital Media Art Creation.” 網際網路技術學刊, vol. 23, no. 1, Jan. 2022, pp. 127–134, 10.53106/160792642022012301013. Accessed 30 Jan. 2022.

Kim, Kwang Gi. “Book Review: Deep Learning.” Healthcare Informatics Research, vol. 22, no. 4, 2016, p. 351, 10.4258/hir.2016.22.4.351. Accessed 26 Nov. 2019.

LeCun, Yann, et al. “Deep Learning.” Nature, vol. 521, no. 7553, May 2015, pp. 436–444, 10.1038/nature14539.

Bengio, Yoshua, et al. Deep Learning. 3 Oct. 2015.

Openai, Ian. NIPS 2016 Tutorial: Generative Adversarial Networks. 2016.

O'shea, Keiron, and Ryan Nash. An Introduction to Convolutional Neural Networks. 2015.

Li, Zewen, and Wenjie Yang. A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. 2021, arxiv.org/ftp/arxiv/papers/2004/2004.02806.pdf.

Gu, Jiuxiang, et al. “Recent Advances in Convolutional Neural Networks.” Pattern Recognition, vol. 77, May 2018, pp. 354–377, 10.1016/j.patcog.2017.10.013.

Wan, Li, and Shuguo Han. Privacy-Preservation for Gradient Descent Methods. 2001, d1wqtxts1xzle7.cloudfront.net/28211813/10.1.1.124.3885-libre.pdf?1390873578=&response-content-disposition=inline%3B+filename%3DPrivacy\_preservation\_for\_gradient\_descen.pdf&Expires=1670770951&Signature=BwICVE0OdShzdchhm3jViDlB1trorJF4rIybHWWOaZjuWZHH7A6hgn5fk3zJkj87aNjM3L7RL7fCqgezLs5QzHsj1dPCZyPtkCua1BeWOOwtQMeuqlseZiPDh~oyX1EW-RnoWFvMnVHHXaTIjmNvglvD8LbIyupcnZ5LfCAoyD8pkEVXyoOqP5FdPpuFDcjJghX4DgdI1upX57~1jDUF4lU0j9Asp7ULW7Vm0lAQTfJMzq7lNbVXoaIU75-jzNxKHvdibSw30Mk8GWpxyYVIQdWSO0ORNtzzxdvfNpqPqTNuzHpQwkiWMF9svT9TdkBRnwwly8d2IRjtzJO0n4c1uA\_\_&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA.

Kang, Yu, and Yiheng Wei. Generalization of the Gradient Method with Fractional Order Gradient Direction. 2018, arxiv.org/pdf/1901.05294.pdf.

J.Nilson, Nils. THE QUEST for ARTIFICIAL INTELLIGENCE a HISTORY of IDEAS and ACHIEVEMENTS. 2009, d1wqtxts1xzle7.cloudfront.net/34400536/ai-libre.pdf?1407538834=&response-content-disposition=inline%3B+filename%3DTHE\_QUEST\_FOR\_ARTIFICIAL\_INTELLIGENCE.pdf&Expires=1671096595&Signature=U7MDPcJ~fjiHGdJmjqVhPNQTJququ9mR4HN3hmXpofmctuFunm0lx-06htbhOxeud~n7xA3FTs796MZEjgOeWPuIOkE~FP~O7K3408KM3rWcYEFA8vve3iaGrMqugJOl~OQeTBwE-sYNTzHgbNpF4TvKj3WhiqZETgsD3RwbzhL-Xz~zl9~m4JtZUCfEPzOZYyuLLUHZe6Zy7HEw3T9OPxWXzd4eQAGCWF8hjkwZK-kXXIMF~EfWrNZfFBZIxAYRFkrDCkBroZDrnSLj9iwcGFbKYeVmGNGfvEF8P7cccza3bXpCPFOwFGB83p-U-tx8WLtfc~InT1ROSMoHHOqrFw\_\_&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA.

Huang, M.H., & Rust, R.T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155–172.

LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521, 436-444.

Cath, C. (2018). Governing artificial intelligence: ethical, legal and technical opportunities and challenges. Philosophical Transactions A: Mathematical Physical and Engineering Sciences, 376(2133), 20180080. doi: <http://10.1098/rsta.2018.0080>

Loureiro, Sandra María, and Iis Tussyadiah. Artificial Intelligence in Business: State of the Art and Future Research Agenda. 2021, s3.eu-central-1.amazonaws.com/eu-st01.ext.exlibrisgroup.com/44SUR\_INST/storage/alma/F8/40/60/A5/3A/5B/0C/83/93/B0/B0/B0/0F/74/D3/1A/Artificial%20Intelligence%20in%20Business\_JBRAccepted.pdf?response-content-type=application%2Fpdf&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Date=20221215T091305Z&X-Amz-SignedHeaders=host&X-Amz-Expires=119&X-Amz-Credential=AKIAJN6NPMNGJALPPWAQ%2F20221215%2Feu-central-1%2Fs3%2Faws4\_request&X-Amz-Signature=8763401629d4fa88a61784e5333e1d99ed03f0544cf7f75043e5185aab02f55d.

Islam, Amirul, et al. HOW MUCH POSITION INFORMATION DO CONVOLUTIONAL NEURAL NETWORKS ENCODE? 2020.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In CVPR, 2016.

Yaniv Taigman, Ming Yang, Marc’Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In CVPR, 2014.

Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In CVPR, 2015.

M. Cheng, N. J. Mitra, X. Huang, P. H. S. Torr, and S. Hu. Global contrast based salient region detection. TPAMI, 2015.

Md Amirul Islam, Mrigank Rochan, Neil DB Bruce, and Yang Wang. Gated feedback refinement network for dense image labeling. In CVPR, 2017.

Zachary C Lipton. The mythos of model interpretability. Queue, 2018.

M. Cornia, L. Baraldi, G. Serra, and R. Cucchiara. Predicting human eye fixations via an lstm-based saliency attentive model. TIP, 2018.

Sen Jia and Neil DB Bruce. Richer and deeper supervision network for salient object detection. arXiv preprint arXiv:1901.02425, 2019.

F Visin, K Kastner, K Cho, M Matteucci, A Courville, and Y Bengio. A recurrent neural network based alternative to convolutional networks. arXiv preprint arXiv:1505.00393, 2015.

Sen Jia and Neil DB Bruce. Eml-net: An expandable multi-layer network for saliency prediction. arXiv preprint arXiv:1805.01047, 2018.

Nicholas Baker, Hongjing Lu, Gennady Erlikhman, and Philip J. Kellman. Deep convolutional networks do not classify based on global object shape. PLOS Computational Biology, 2018.

Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In ICCV, 2017.

Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning requires rethinking generalization. arXiv preprint arXiv:1611.03530, 2016.

Geoffrey Hinton, Simon Osindero, Max Welling, and Yee-Whye Teh. Unsupervised discovery of nonlinear structure using contrastive backpropagation. Cognitive science, 2006.

Dumitru Erhan, Yoshua Bengio, Aaron Courville, and Pascal Vincent. Visualizing higher-layer features of a deep network. University of Montreal, 2009.

Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In ECCV, 2014.

M. D. Zeiler, G. W. Taylor, and R. Fergus. Adaptive deconvolutional networks for mid and high level feature learning. In ICCV, 2011.

Alber, Maximilian, et al. “INNvestigate Neural Networks!” Journal of Machine Learning Research, vol. 20, 2019, pp. 1–8, www.jmlr.org/papers/volume20/18-540/18-540.pdf.

A¨aron Van Den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio. arXiv preprint arXiv:1609.03499, 2016.

Yann A LeCun, L´eon Bottou, Genevieve B Orr, and Klaus-Robert M¨uller. Efficient backprop. In Neural networks: Tricks of the trade, pages 9–48. 2012.

Yann A LeCun, Yoshua Bengio, and Geoffrey E Hinton. Deep learning. Nature, 521(7553): 436–444, 2015.

J¨urgen Schmidhuber. Deep learning in neural networks: An overview. Neural networks, 61: 85–117, 2015.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems 25, pages 1097–1105, 2012.

Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. 2018 IEEE Conference on Computer Vision and Pattern Recognition, pages 8697–8710, 2018.

Kristof T Sch¨utt, Farhad Arbabzadah, Stefan Chmiela, Klaus-Robert M¨uller, and Alexandre Tkatchenko. Quantum-chemical insights from deep tensor neural networks. Nature Communications, 8:ID: 13890, 2017.

Gr´egoire Montavon, Matthias Rupp, Vivekanand Gobre, Alvaro Vazquez-Mayagoitia, Katja Hansen, Alexandre Tkatchenko, Klaus-Robert M¨uller, and Anatole Von Lilienfeld. Machine learning of molecular electronic properties in chemical compound space. New Journal of Physics, 15(9):ID: 095003, 2013.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems 25, pages 1097–1105, 2012.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In Advances in Neural Information Processing Systems. 2672–2680.

Hao Dong, Simiao Yu, Chao Wu, and Yike Guo. 2017. Semantic image synthesis via adversarial learning. In Proceedings of the IEEE International Conference on Computer Vision. 5706–5714.

Gintare Karolina Dziugaite, Daniel M. Roy, and Zoubin Ghahramani. 2015. Training Generative Neural Networks via Maximum Mean Discrepancy Optimization. arXiv:1505.03906. Retrieved from <https://arxiv.org/abs/1505.03906>.

Ian Goodfellow. 2016. NIPS 2016 Tutorial: Generative Adversarial Networks. arXiv:1701.00160. Retrieved from <https://arxiv.orb/abs/1701.00160>.

Eoin Brophy, Zhengwei Wang, and Tomas E. Ward. 2019. Quick and Easy Time Series Generation with Established Image-based GANs. arXiv:1902.05624. Retrieved from <https://arxiv.org/abs/1902.05624>.

Zihang Dai, Zhilin Yang, Fan Yang, William W. Cohen, and Ruslan R. Salakhutdinov. 2017. Good semi-supervised learning that requires a bad GAN. In Advances in Neural Information Processing Systems. 6510–6520.

Zeyuan Chen, Shaoliang Nie, Tianfu Wu, and Christopher G. Healey. 2018. High Resolution Face Completion with Multiple Controllable Attributes via Fully End-to-end Progressive Generative Adversarial Networks. arXiv:1801.07632. Retrieved from <https://arxiv.org/abs/1801.07632>.

Junsuk Choe, Song Park, Kyungmin Kim, Joo Hyun Park, Dongseob Kim, and Hyunjung Shim. 2017. Face generation for low-shot learning using generative adversarial networks. In Proceedings of the IEEE International Conference on Computer Vision. 1940–1948.

Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Kim, and Jaegul Choo. 2018. StarGAN: Unified generative adversarial networks for multi-domain image-to-image translation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 8789–8797.

CROWLEY, E. J., AND ZISSERMAN, A. In search of art. In European Conference on Computer Vision (2014), Springer, pp. 54–70.

GOODFELLOW, I., POUGET-ABADIE, J., MIRZA, M., XU, B., WARDE-FARLEY, D., OZAIR, S., COURVILLE, A., AND BENGIO, Y. Generative adversarial nets. Advances in neural information processing systems 27 (2014), 2672–2680.

LANG, S., AND OMMER, B. Reflecting on how artworks are processed and analyzed by computer vision: Supplementary material. In Proceedings of the European Conference on Computer Vision (ECCV) (2018), pp. 0–0.

GRAHAM, D. J., HUGHES, J. M., LEDER, H., AND ROCKMORE, D. N. Statistics, vision, and the analysis of artistic style. Wiley Interdisciplinary Reviews: Computational Statistics 4, 2 (2012), 115–123.