Afyon Kocatepe Üniversitesi Fen ve Mühendislik Bilimleri Dergisi

Afyon Kocatepe University Journal of Science and Engineering

AKÜ FEMÜBİD **23** (2023) 035103 (671-676)

AKU J. Sci. Eng. **23** (2023) 035103 (671-676)

DOI: 10.35414/ akufemubid.1269356

Araştırma Makalesi / Research Article

End-to-End Artworks Generation Via Deep Convolutional Based Generative Adversarial Networks

Nazlı TURHAN[1*], Ahmet Haşim YURTTAKAL[2]

[1]*Afyon Kocatepe University, Institute of Science, Internet and Information Technologies Management, Afyonkarahisar.*

[2]*Afyon Kocatepe University, Engineering Faculty, Department of Computer Engineering, Afyonkarahisar.*

Corresponding author e-mail: av.nazliturhan@gmail.com.tr ORCID ID: http://orcid.org/0000-0002-0854-7583*

ahyurttakal@aku.edu.tr ORCID ID: http://orcid.org/0000-0001-5170-6466

Geliş Tarihi: 27.09. 2022 *Kabul Tarihi: 16.05.2023*

Keywords
Artworks; Generative Adversarial Networks; End-to-End; Artificial Intelligence.

Abstract

While artificial intelligence (AI) technologies are used in many fields such as health, education, art and continue to develop rapidly, emerging artificial intelligence solutions are also being addressed by different disciplines, such as informatics and law. Apart from the problems of legal rules' having access to the speed of social change, the search of a legal infrastructure that is suitable for keeping up with these changes has started to make itself felt in recent years. In the study, the technical stages of digital artworks created by using contentious producer networks from deep learning algorithms were discussed and evaluated within the scope of intellectual and artistic works law. In the study, 6989 abstract and portrait paintings, which are a subset of the Wiki-Art dataset, were used. As a result, it has been seen that the number of images in the dataset affects the originality of the outputs. It is thought that the proposed method can be applied to different branches of art and can give art lovers a different perspective.

Derin Evrişim Tabanlı Çekişmeli Üretici Ağları İle Uçtan Uca Sanat Eserleri Üretimi

Anahtar Kelimeler
Sanat Eserleri; Çekişmeli Üretici Ağlar; Uçtan uca; Yapay Zeka.

Öz

Yapay zeka (AI) teknolojileri sağlık, eğitim, sanat gibi birçok alanda kullanılıp hızla gelişmeye devam ederken ortaya çıkan yapay zeka çözümleri, bilişim hukuku gibi farklı disiplinler tarafından da ele alınmaktadır. Hukuk kurallarının sosyal değişimin hızına erişim sorunları bir yana, değişime ayak uydurmaya müsait bir hukuki alt yapının varlığının araştırılması da son yıllarda önemini hissettirmeye başlamıştır. Çalışmada derin öğrenme algoritmalarından çekişmeli üretici ağlar kullanılarak oluşturulan dijital sanat eserlerinin teknik aşamaları ele alınarak fikir ve sanat eserleri hukuku kapsamında değerlendirilmiştir. Çalışmada Wiki-Art veri kümesinin bir alt kümesi olan 6989 adet soyut ve portre tablolar kullanılmıştır. Sonuç olarak veri kümesindeki görüntü sayısının çıktıların orijinalliğine etki ettiği görülmüştür. Önerilen yöntemin farklı sanat dallarına uygulanabileceği ve sanatseverlere farklı bir bakış açısı kazandırabileceği düşünülmektedir.

1. Introduction

Artists who create works of art reveal the information they have learned throughout their lives by processing them with the creative aspects of their minds. It is impossible for someone who has never seen a tree to draw the concept of a tree on a table or a natural water element as a stream. On the other hand, the potential effects of groundbreaking artificial intelligence on art and creativity are followed with interest by scientists (Mazzone and Elgammal 2019).

Psychologists define the concept of intelligence as a process in which many different elements come together. Learning, reasoning, problem-solving, perceiving and using language; are inseparable basic elements of intelligence (Terman 1948). Artificial Intelligence, on the other hand, is a situation similar to the working process of human intelligence, extracting unknown information from known data (Hunt 2014). Machine learning algorithms focus on learning by finding relationships from patterns in datasets (Zhou 2021). Machine learning is used in various fields such as healthcare, natural language processing, image processing, agriculture (Hayit *et al*. 2021; Akmese 2022; Aslan *et al*. 2018). Machine learning methods performed by labelling the output with the desired value are called Supervised Learning, while machine learning methods performed without labelling the output data are called Unsupervised Learning (Saravanan and Sujatha 2018). Deep Learning is a sub-branch of machine learning in which complex structures are learned in datasets (Alaskar and Saba 2021). It has been found that deep learning algorithms trained using large-scale data perform significantly better than classical image processing techniques (Wason 2018). The first image generation model of deep networks was proposed in 2014 (Goodfellow *et al*. 2014).

Turhan and Bilge (2020) obtained a high-resolution image on the MNIST dataset using a Generative Network and Autoencoder hybrid. Xue (2021) proposed a two-step GAN algorithm consisting of Sketch and Paint stages on a dataset consisting of 2192 images. Roziere *et al*. (2020) proposed an evolution-based generative network on different data sets such as cat, dog, horse, and face. Chen *et al*. (2020) proposed generative networks with style transfer to produce works of art. Shahriar (2022) presented a comparative survey analysis of Gan Networks' production of different artworks.

In this study, Deep Convolutional Generative Adversarial Networks (DCGANs) were proposed for producing original artworks on the Wiki-Art dataset with access for academic research. Remarkable works were obtained in printouts and presented to the attention of art lovers.

The data set and the DCGANs are presented in the second part of the article, while the outputs obtained in the third part are presented. In the last section, a discussion and conclusion are given.

2. Material and Methods

This section presents the dataset used in the study and the proposed architecture's basic structure.

2.1 Dataset

Two datasets consisting of abstract paintings and portraits were used in the study. Both datasets are subsets of the Wiki-Art Visual Art Encyclopedia dataset (Int. Source 1). The number of abstract artworks in the datasets feeding the proposed model is 2872, and the number of portrait artworks is 4117. Artworks have different width and height values. Sample images from the datasets are given in Figure 1.

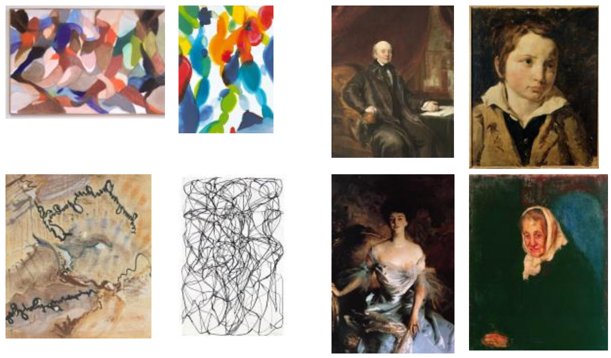

Figure 1. Sample Images from the Datasets

2.2 Deep Convolutional Generative Adversarial Networks (DCGANs)

Generative Adversarial Networks (GANs) are a type of deep learning structure that generates data with similar properties to the fed dataset. Networks of GANs consist of two different network structures working together. One of these network structures, the Generator network, generates data similar to the data in the dataset from randomly generated noise data.

The generator network is Unsupervised Learning. The discriminator network distinguishes whether the data is real or generated. Discriminator network is Supervised Learning (Radford *et al*. 2015). The DCGAN structure is given in Figure 2.

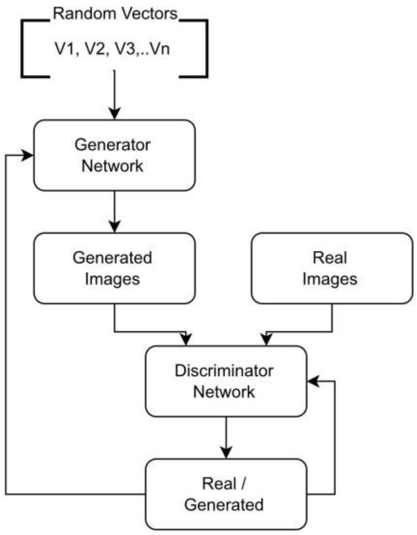

Figure 2. The GAN Structure

Discriminator output is a binary classification as real or generated and is denoted by Y. Equation 1 gives the loss function for the generator network, and Equation 2 gives the loss function for the discriminator network. Here δ denotes the loss function, and μ denotes the mean operation. $Yreal$ represents the probability that the discriminator network output is real images, while $Yfake$ represents the probability of generated images.

$$\delta gen = -\mu(\log(Yfake)) \tag{1}$$

$$\delta disc = -\mu(\log(Yreal)) - \mu(\log(1 - Yfake)) \tag{2}$$

The scoring metric measures how well the generator and discriminator networks have achieved their goals. In Equation 3, the formula of the scoring metric of the Generator network is given, while in Equation 4, the formula of the scoring metric of the Discriminator network is given.

$$\partial gen = \mu(Ygenerated) \tag{3}$$

$$\partial disc = \frac{1}{2}\mu(Yreal) + \frac{1}{2}\mu(1 - Ygenerated) \tag{4}$$

3. Simulation Results

The developed method has been tested on a personal notebook computer with an i5-1035G1 processor and 8GB RAM. The structure of the Generator network of the proposed method consists of 13 layers. The layers are given in detail in Table 1.

Table 1. Generator Network

No	Layer Name	Layer Description
1	Input	100 features
2	Reshape	Reshape 4x4x512
3	Convolution	numFilter=256 Filter Size=5×5 Striding= [1 1] Cropping = [0 0 0 0]
4	Normalization	Batch normalization
5	Activation	ReLU
6	Convolution	numFilter=128 Filter Size=5×5 Stride=[2 2] Cropping ='same'
7	Normalization	Batch normalization
8	Activation	ReLU
9	Convolution	numFilter=64 Filter Size=5×5 Striding= [2 2] Cropping='same'
10	Normalization	Batch normalization
11	Activation	ReLU
12	Convolution	numFilter=3 Filter Size=5×5 Striding= [2 2] Cropping = 'same'
13	Activation	Hyperbolic tangent

There are four convolutions, four activation and three normalization layers in the Generator network of the model. While the hyperbolic tangent activation function is used in the last layer, ReLu is used in other activation functions. The structure of the Discriminator network of the proposed method consists of 15 layers. The layers are given in detail in Table 2.

Table 2. Discriminator Network

No	Layer Name	Layer Description
1	Input	64×64×3 images
2	Dropout	50%
3	Convolution	numFilter=64 Filter Size=5×5 Striding= [2 2] Padding='same'
4	Activation	Leaky ReLU Scale=0.2
5	Convolution	numFilter=128 Filter Size=5×5 Striding=[2 2] Padding='same'
6	Normalization	Batch normalization
7	Activation	Leaky ReLU Scale=0.2
8	Convolution	numFilter=256 Filter Size=5×5 Striding=[2 2] Padding='same'
9	Normalization	Batch normalization
10	Activation	Leaky ReLU Scale=0.2
11	Convolution	numFilter=512 Filter Size=5×5 Striding=[2 2] Padding='same'
12	Normalization	Batch normalization
13	Activation	Leaky ReLU Scale=0.2
14	Convolution	numFilter=1 Filter Size=4×4 Striding=[1 1] padding=[0 0 0 0]
15	Activation	Sigmoid

There are five convolutions, five activation and three normalization layers in the Discriminator network of the model. While the Sigmoid Activation function is used in the last layer, Leaky Relu is used in other activation functions. The hyperparameters of the proposed model are given in Table 3.

Table 3. Hyper-parameters

Parameter	Value
Epoch	500
Minibatch	128
Learn Rate	0.0002
gradientDecayFactor	0.5
squaredGradientDecayFactor	0.999
validationFrequency	100

Hyperparameters can be changed and different images can be obtained in different trials. Transforms have been applied to the images so that the discriminator network cannot easily learn real and generated images. Generated abstract pictures are given in Figure 3.

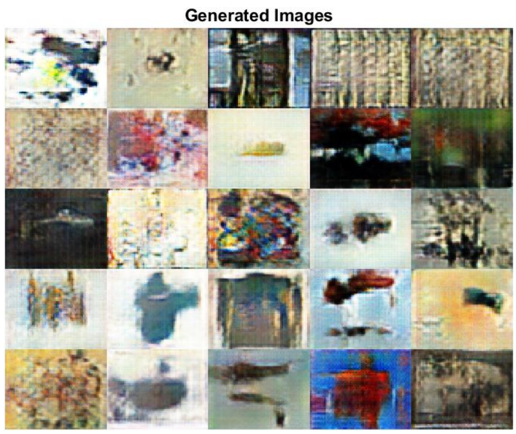

Figure 3. Generated Abstract Images

When the produced abstract artworks are examined, it is seen that some similar works have been produced. The reason for this is considered to be that the data set is relatively small. In some abstract paintings, the colour variety is limited, and there are also images where white colour is dominant. This situation had a direct effect on the output images. On the other hand, generated portrait pictures are given in Figure 4.

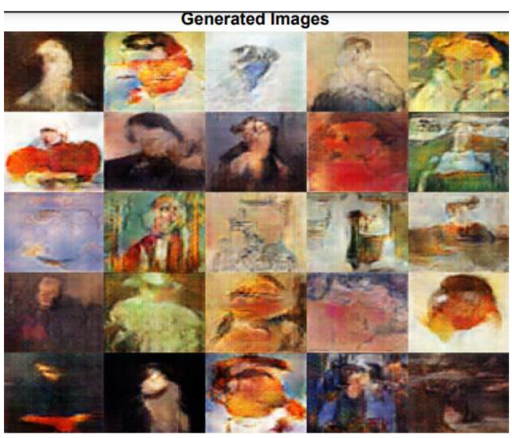

Figure 4. Generated Portrait Images

When the portrait artworks produced are examined, it is seen that they are mostly different, and some of them resemble human beings. The reason for this is considered to be because the data set is relatively large. Generator and discriminator scores are given in Figure 5.

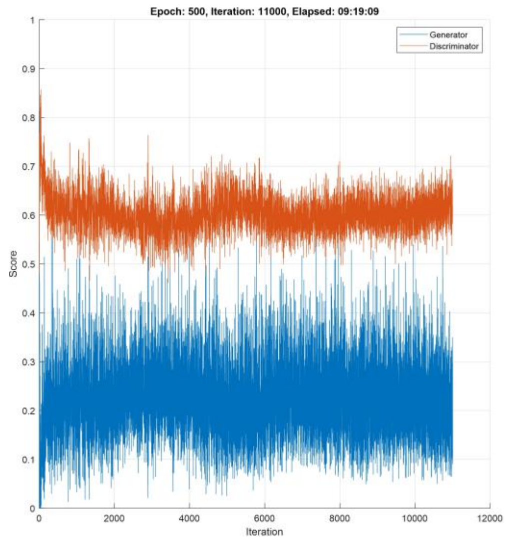

Figure 5. Generator-Discriminator Score

During the training period, which lasted approximately 9 hours, it was observed that the generator and discriminator networks were competing and produced score values close to each other in some iterations. This shows that the education process is realized as desired.

4. Discussion and Conclusion

Humans have begun to experience that there may be beings who think and make decisions other than themselves with artificial intelligence and machine learning technologies. In machine learning, the information in the outside world is digitized and taught to a machine. Deep Learning, on the other hand, is closely related to representational Learning, unlike machine learning. This process can be compared to a baby in the learning age, experiencing the outside world step by step and coding it into his conscious system. Therefore, it can be said that the paintings painted by the painters present the already existing information, which they have previously encoded in their memories, in line with a composition. One of the most interesting and attractive topics of deep Learning is GAN structures.

In this study, artworks were produced using the DCGAN structure. The images in our dataset are the Wiki-Art dataset, and there are artworks by artists such as Pablo Picasso, Claude Monet, and Salvador Dali. Our primary motivation in this study was to produce new images, present them to art lovers, and evaluate the produced works in the context of intellectual property law.

According to the 5846 Law on Intellectual and Artistic Works, work refers to all kinds of intellectual and artistic products considered works of science and literature, cinema, and music with the owner's characteristics. While there are clear lines on conventional works of art in the Law on Intellectual and Artistic Works, there is no regulation on works of art created through machine learning yet.

For this reason, although there are legal rights to the pictures used in our data set, the artists who made them have legal rights; it is impossible to evaluate this study by our current law since the pictures created as a result of machine learning are other creations.

Intellectual efforts created through artificial intelligence technology are a value that should be protected when directed to the appreciation of society. While the regulations protect intellectual and artistic works, the value protected here is not only creations but also society's appreciation. In other words, art and society have mutually created each other for centuries. Therefore, in addition to making legal regulations that act with the spirit of protecting all kinds of artificial intelligence products offered to the public, there is a need for new initiatives that support artificial intelligence and recognize it in the legal world and make room for it. Instead of defining artificial intelligence as a separate entity from humans, it should not be ignored that the features that exist in humans and that have not yet been noticed have benefits that encourage them to emerge and gain value. However, while the legal framework for machine learning-supported creations is being drawn, it is thought that a legal step is needed to not only be limited to the regulations focused on the creations in question but also to respect and protect the appreciation of the society.

In conclusion, the proposed method has obtained interesting images on the pictures. It has been observed that more different images are obtained, especially in portrait tables with more data than abstract pictures. In future studies, it is thought to be applied to different branches of art, such as literature, poetry and music.

5. References

Akmeşe, Ö. F., 2022. Diagnosing Diabetes with Machine Learning Techniques. Hittite Journal of Science and Engineering, **9(1)**, 9-18.

Alaskar, H., & Saba, T., 2021. Machine Learning and Deep Learning: A Comparative Review. *Proceedings of Integrated Intelligence Enable Networks and Computing: IIENC 2020*, 143-150.

Aslan, O., Gunal, S., & Dincer, B. T., 2018. A computational morphological lexicon for turkish: Trlex. Lingua, **206**, 21-34.

Chen, H., Zhao, L., Qiu, L., Wang, Z., Zhang, H., Xing, W., & Lu, D., 2020. Creative and diverse artwork generation using adversarial networks. *IET Computer Vision*, **14(8)**, 650-657.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y., 2014. Generative adversarial networks 2014. *arXiv preprint arXiv:1406.2661*, *1406*.

Hayit, T., Erbay, H., Varçın, F., Hayit, F., & Akci, N., 2021. Determination of the severity level of yellow rust disease in wheat by using convolutional neural networks. Journal of Plant Pathology, **103(3)**, 923-934.

Hunt, E. B., 2014. *Artificial intelligence*. Academic Press.

Mazzone, M., & Elgammal, A., 2019. Art, creativity, and the potential of artificial intelligence. In: Arts. MDPI, **8(1)**.

Terman, L. M., 1948. The measurement of intelligence, 1916.

Turhan, C.G., & Bilge, H.Ş., 2020. Scalable image generation and super resolution using generative adversarial networks. *Journal of the Faculty of Engineering and Architecture of Gazi University*, ***35*****(2)**.

Radford, A., Metz, L., & Chintala, S., 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.

Roziere, B., Teytaud, F., Hosu, V., Lin, H., Rapin, J., Zameshina, M., & Teytaud, O., 2020. Evolgan: Evolutionary generative adversarial networks. In *Proceedings of the Asian Conference on Computer Vision*.

Saravanan, R., & Sujatha, P., 2018,. A state of art techniques on machine learning algorithms: a perspective of supervised learning approaches in data classification. In *2018 Second international conference on intelligent computing and control systems (ICICCS),* IEEE, 945-994.

Shahriar, S., 2022. GAN computers generate arts? a survey on visual arts, music, and literary text generation using generative adversarial network. *Displays*, 102237.

Wason, R., 2018. Deep learning: Evolution and expansion. *Cognitive Systems Research*, ***52***, 701-708.

Xue, A., 2021. End-to-end chinese landscape painting creation using generative adversarial networks. In *Proceedings of the IEEE/CVF Winter conference on applications of computer vision,* 3863-3871.

Zhou, Z. H., 2021. *Machine learning*. Springer Nature.

Int. Sources

1-https://www.wikiart.org/ (07.03.2023)