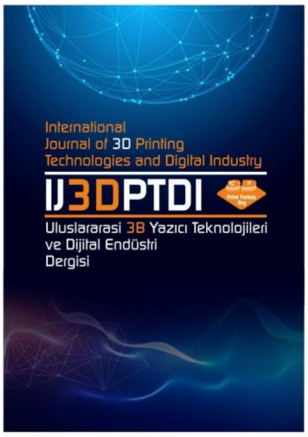

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NATURE-INSPIRED DESIGN IDEA GENERATION WITH GENERATIVE ADVERSARIAL NETWORKS

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ABSTRACT

Generating new, creative, and innovative ideas in the early stages of the design process is crucial for developing better and original products. Human designers may become too attached to specific design ideas, preventing them from generating new concepts and achieving ideal designs. To come up with original design ideas, a designer needs to have a creative mind, as well as knowledge, experience, and talent. Verbal, written, and visual sources of inspiration can also be valuable for generating ideas and concepts. This study presents a visual integration model that uses a data-supported Artificial Intelligence (AI) method to generate creative design ideas. The proposed model is based on a generative adversarial network (GAN) that combines target object and biological object images to produce new creative product images inspired by nature. The model was successfully applied to an aircraft design problem and the resulting sketches inspired designers to generate new and creative design ideas and variants in a case study. It was seen that this approach improved the quality of the ideas produced and simplified the idea and concept generation process.

Keywords: Generative Adversarial Network, Biomimicry, Idea Generation.

1. INTRODUCTION

The design process involves several stages, including task clarification, conceptual design, embodiment design, and detailed design [1]. Conceptual design is a crucial stage in which the problem definition and functions, solution principles search, various design options creation, and evaluation and selection take place. Traditional and modern techniques can be used in this stage to arrive at the ideal concept. Traditional product and engineering design utilize scientific, intuitive, experiential, and creative knowledge and methods, while modern methods employ information technologies and Artificial Intelligence (AI) to shorten processes, increase creativity, obtain sensitive results, and reduce costs [2].

The term "Artificial Intelligence" (AI) refers to computer programs that simulate specific mental functions and behaviors observed in living beings. These programs are used in various disciplines for learning, understanding, prediction, problem-solving, suggestion, and decision-making [3]. Although the term AI was first used in 1956, recent developments in computer technology, such as increased processing speed and memory, and easier access to data have led to significant advancements in AI over the last 15 years. AI techniques have also become increasingly prevalent in engineering and product design processes, allowing software to compare, evaluate, and estimate design options, generate innovative and creative ideas, and enhance creativity capabilities when integrated into various methods.

With the development of machine learning and deep learning methods, intelligent software can now support creative design activities such as ideation, concept creation, and inspiration [15, 17]. One such model is the use of generative adversarial networks (GANs) to generate original design ideas. GANs can combine biological and target objects to enhance designer creativity in idea generation [18]. The visual concept assembly method is a powerful tool that allows designers to create visually appealing designs and communicate information effectively. The integration of data-driven artificial intelligence and visual concepts provides an advantage over previous studies as it has the potential to simplify complex information, create compelling designs, and emotionally connect with audiences. By combining visual and textual elements, designers can create catchy and effective designs that engage the audience emotionally.

2. RELATED STUDIES

Creating creative and original ideas is very important in the product design process. However, because of psychological inertia, it could only sometimes be feasible to develop original and unique ideas [4]. This situation can be an obstacle in the conceptual design process to focus on an idea and reach the ideal/perfect design [5, 6]. Employing verbal, textual, and visual sources of inspiration might help to get beyond this conceptual production roadblock. [7-9]. Recently, AI-powered software has also been used to create inspiration for designers. For example, Wang et al. [10] created a data-dependent idea network employing resources from the web and scientific publications. They, therefore, sought to lessen the workload associated with the literature review during the early design phase. Designers developed them as a source of inspiration by recognizing vitally significant conceptual words. This machine learning-based approach measures similarity (proximity) between concepts. Thus, creativity levels can be measured by detecting close-far relationships. A program named "The Combinator" was created by Han et al. [4] to combine concepts without obvious relationships. Semantic networks connect the data that web browsers collect and evaluate using tools for natural language processing. It is possible to develop inventive product ideas by combining many comparable ideas in new ways [11, 12]. " The Combinator " sparks creativity by merging text and visual data in various ways. It makes it easier for designers to explore the design space for solutions. Jin and Dong [13] analyzed the RedDot award-winning 998 products with the help of QSR NVivo data analysis software and created ten new design heuristics cards [14]. With text mining, machine learning, and natural language processing software, ontology-based approaches may identify links between concepts. Shi et al. Developed a design and engineering-oriented unsupervised ontology network called WordNet [15, 17].

Bell and Bala [16] aimed to inspire designers by using Siamese CNN trained with real product photos. Chen et al. [18] tried to create inspiration for designers with two different models. The initial model is A semantic network developed using data mining and NLP approaches. Semantic networks are a useful tool for locating and displaying related concepts, Close and distant concept interactions facilitate the rapid and effortless generation of creative ideas. The visual concept combination model is another instrument for inspiration generation. The GANs model creates new pictures combining these two items after being trained using photos of a biological thing and a target object. Both biological object and target object attributes are present in the new photos. Thus, the designer's imagination might generate fresh thoughts and associations. The quantity and variety of training data are key factors in model performance.

Inspiration studies generally include machine learning, deep learning, and natural language processing algorithms. As these methods become widespread and access to data/information becomes easier may also shorten the market research and literature review process for new product design. In addition, semantic networks can be created with natural language processing algorithms. These networks can also generate new and creative ideas by revealing the relationship between design concepts. With various combinations of visual data, new connections of concepts can be discovered. In this study, designers were stimulated using the deep learning model GAN at the conceptual design stage. GAN by fusing with images of the goal and natural object, it seeks to generate new shapes in the designer's head. The validity of the method is demonstrated in an aircraft design problem.

2.1. Deep Learning

Machine learning is the general name of statistical AI methods that can make predictions and inferences based on data [19-21]. Unlike traditional programming, it does not need an exact algorithm to learn [22]. Instead, it detects patterns in the data set and uses these patterns to interpret future data. Just like the human learning mechanism, the ability to interpret improves as the number of data increases. The increase in the amount of data, ease of access to big data, and increase in computer performance increase the success of machine learning prediction and identification. On the other hand, deep learning is a machine learning method with multi-layered neural networks. Some of these models are Autoencoder (AE), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) [23]. Deep learning algorithms are very successful in image classification, object recognition, voice recognition, face recognition, and language translation. In the design field, topology optimization, generating design concepts, computational design, computer-aided engineering, and simulation tasks can be done with deep learning methods [24]. CNNs are used in 2D and 3D image recognition and classification tasks [22, 25]. On the other hand, GANs have provided a new perspective on deep learning. A single architecture contains two distinct networks known as the generator and discriminator [26]. Operations like producing previously unimagined pictures, boosting the resolution of already existent images, and text-to-image translation are all possible using generative contention networks [27]. In addition, operations such as converting sketches to colour images, coloring black and white photographs can be done with GANs [28].

Machine learning algorithms also have some downsides. For example, huge amounts of data are required to increase learning success. As the number of data increases, processing times may also increase [29]. Creating labeled datasets is cumbersome. It needs to be fully explained how machine learning algorithms achieve results. Although they have a high success rate, there is always the possibility of error [30].

3. VISUAL CONCEPT INTEGRATION

The cognitive process that provides the ability to develop new, original and useful ideas is called creativity. Creative ideas and concepts produced during the conceptual design phase significantly contribute to the final product's success [31, 32]. Although the conceptual design is a cognitive process, verbal, written, and visual sources of inspiration are generally used to produce creative ideas and concepts [7-9]. One of them is Arthur Koestler's "bisociation" model, which will create inspiration in the designer's mind by bringing together different concepts [33]. A data-driven visual concept unification model was created to facilitate the creative thinking process based on this model. Two images that are not closely related can be combined to create a new image. This new image must carry both conceptual features in a certain proportion.

GAN, one of the current and promising deep learning methods, can contribute to the solution to this design problem. GAN; It is a new deep learning algorithm used to generate and edit data such as images, audio, video, and 3D models. A standard GANs architecture includes two deep neural networks: a generator and a discriminator. The generating network is trained with images made up of random pixels and creates new (fake) images. The discriminatory network tries to separate the produced images from the real ones. These two networks' educational purposes are to develop generation and discrimination skills, respectively [34]. Thus, new and realistic visuals can be produced. In the design process, computer-aided engineering/design tasks such as inspiration generation, idea/concept generation, and computational (computational) design topology optimization can be easily done with the help of GAN [35, 36, 37].

A dataset is created to develop a visual combination model by collecting biological and target object images. The normalization of the resulting images follows a series of data pre-processing. Finally, a noise distribution is used to generate new images. This study uses the Deep Convolutional Generative Adversarial Network (DCGAN) model to train generator and discriminator networks.

The overall approach for training a DCGAN model involves updating the discriminator and generator models in an alternating manner using their respective loss functions and optimizers. The loss functions determine how well the models are able to differentiate between real and fake data, while the optimizers modify the weights of the models to minimize the loss. The ultimate objective is to achieve an equilibrium where the generator produces realistic images that deceive the discriminator [38,39]. To begin training a DCGAN model, we first initialize the generator and discriminator models with random weights. Next, we define loss functions to measure the performance of each model and optimizers to update the network weights based on the loss functions. Finally, we create a loop that iterates until convergence or a maximum number of iterations is reached [40]. The specific steps for training the DCGAN are shown in the following pseudo-code.

- Initialize generator G and discriminator D with random weights
  G = Generator()
  D = Discriminator()
- Define loss functions L_G and L_D for G and D respectively
  L_G = ...
  L_D = ...
- Define optimizers O_G and O_D for G and D respectively
  O_G = ...
  O_D = ...
- Loop until convergence or maximum number of iterations N for i in range(N):
  - Generate a batch of fake data x_fake using G
    x_fake = G.generate(batch_size)
  - Get a batch of real data x_real from training set X_train
    x_real = X_train.sample(batch_size)
  - Calculate discriminator outputs y_fake and y_real for x_fake and x_real respectively
    y_fake = D.predict(x_fake)
    y_real = D.predict(x_real)
  - Calculate discriminator loss L_D(y_fake, y_real)
    d_loss = L_D(y_fake, y_real)
  - Update discriminator weights w_D using O_D(d_loss, w_D)
    w_D = O_D(d_loss, w_D)
  - Generate another batch of fake data x_fake using G
    x_fake = G.generate(batch_size)
  - Calculate generator output y_gen using D
    y_gen = D.predict(x_fake)
  - Calculate generator loss L_G(y_gen)
    g_loss = L_G(y_gen)
  - Update generator weights w_G using O_G(g_loss, w_G)
    w_G = O_G(g_loss, w_G)
- Save or display the final generator model
  save_or_display(generator)

4. RESULTS

The proposed DCGAN architecture consists of a discriminator and a generator, as shown in Figure 1. Here, the generating network learns to generate new data using the Gaussian point distribution. First, a tensor of n x n x m size is created by reshaping a Z-dimensional random pixel set. Then, a new n x n x 1-dimensional tensor (fake image) is obtained with deconvolution layers. While the LeakyReLU activation functions transfer information from one de-convolution layer to the other, the tanh activation function is used in the last layer. The number of layers, kernels (m), and tensor dimensions specified here are determined intuitively based on experience [18].

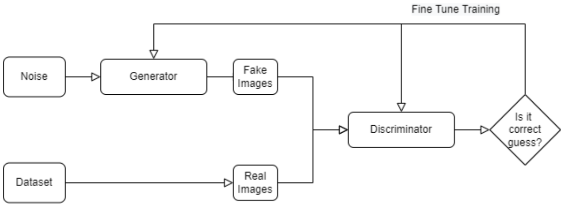

Figure 1. A schematic representation of the GAN model

On the other hand, the discriminative network, which includes a classical CNN architecture, is tried to distinguish between the images from the training set and the fake images. The n x n x 1-dimensional image is converted into an n x n x 64-dimensional tensor with convolution layers. Then, this tensor is flattened into a one-dimensional matrix. A fully connected neural network performs the classification (real/fake) process in the final stage. To increase the performance of these two networks, the DCGAN model is trained with the classical loss function shown in equation 1 [38]. Min and max mean minimizing Generator (G) loss and maximizing Discriminator (D) loss. Here x denotes the real images, and z denotes the noise input [27]. Adam optimization approach was used for model training. A learning rate of 0,0001 was preferred for training batch size 128. The training process is stopped after 1.000 cycles.

$$\min\max(D,G) = E_x\left[\log\left(D(x)\right)\right] + E_z\left[\log\left(1 - D\left(G(z)\right)\right)\right] \quad (1)$$

A case study was conducted to demonstrate the success of this deep learning model in generating design concepts. A visual combination model inspired designers in an aircraft form design problem. In this context, the great solutions in nature can be a source of inspiration in design. It is aimed to adapt the form features of sharks, which move quickly and can maneuver underwater, to the aircraft form design.

Initially, 2.964 aircraft (target object) and 3.013 sharks (biological object) images were combined into a dataset. These images, which have different image sizes, were converted to 128 x 128 x 3 sizes for model training. Some of the normalized airplane and shark images collected are shown in Figure 2. The generative deep learning model was trained using these images with 1.000 cycles. This proposed model can automatically generate an unlimited number of biologically inspired images after training [24]. Although these images produced by the generative model do not have a clean/clear image, they include features such as color, shape, and texture of sharks and planes (Figure 3).

Figure 2. Some of example images taken from the dataset

Figure 3. Bio-inspired visuals generated by the generative model

The success of creating a new concept from the biologically inspired visuals created with the deep learning-supported visual combination model has been examined with an experimental study. In other words, it was examined to what extent these biologically inspired visuals, which include a combination of airplanes and sharks, would inspire designers during the design Process [17]. For this purpose, 2 final year students of the Department of Industrial Design Engineering were given these new images and asked to use them in creating new design concepts. Students were asked to first examine the images and choose the ones that evoked the design concept. Then, inspired by these selected images, they created new aircraft form variants. Thus, it was tried to develop new, original and creative ideas with the first images that were automatically created with the help of AI and the associations (inspirational sparks) created in the mind of the designer. The images generated by the generative model can offer unique potential ideas for different shark and airplane combinations. Some of the images produced by this model and the concepts inspired by these images are shown in Figure 4.

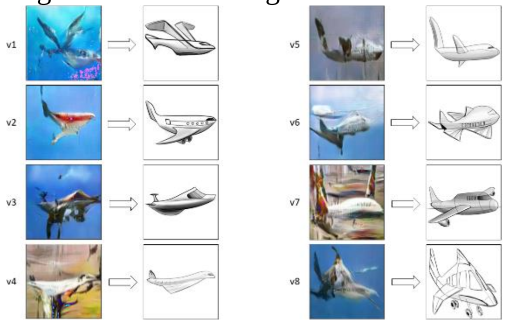

Figure 4. Visuals generated by the visual combination model (on the left side), and concept variants created by the designer (on the right side).

5. DISCUSSION

This study demonstrates the potential of DCGAN architecture to create nature-inspired design concepts [18]. By leveraging a dataset of aircraft and shark images, the generative deep learning model successfully generated a diverse range of visuals that combined the features of both entities. While not completely clean or clear, these images contain key features such as the color, shape and texture of sharks and planes [17].

An experimental study to evaluate the effect of these nature-inspired images on the design process has yielded promising results. When provided with the generated images, industrial design engineering students could select those that resonated with their design concepts and subsequently create novel aircraft form variants inspired by the visuals. This demonstrates the efficacy of the generative model in sparking creative associations in designers' minds and fostering innovative ideas' development [42].

Despite the generative model's success in producing bio-inspired images, the rendered images need improvement. Future research could focus on refining the DCGAN architecture or exploring alternative generative models to enhance the resolution and detail of the generated visuals. Additionally, expanding the dataset to include a wider variety of biological entities or exploring other design domains could further enrich the creative possibilities offered by the model. Furthermore, the experimental study in this research was limited to a small sample of design students. Future investigations could involve a more extensive and diverse group of participants to assess the generalizability of the findings and better understand the impact of AI-generated visuals on various stages of the design process. This could lead to the development of more sophisticated generative models that cater to the specific needs of designers across different disciplines and design challenges.

6. CONCLUSION

This study presents a deep learning-based visual concept merging model to produce new and creative design concepts [41]. The GAN-based algorithm synthesized "airplane" and "shark" visuals to generate ideas for a design task. Since a clear relationship cannot be established between the concepts in the classical idea generation process, the concepts produced are limited in number and have similar features. This algorithm, on the other hand, can easily generate visual stimuli to generate ideas and increase the innovation level and quality of the ideas generated. Therefore, it can increase the designer's potential to create new and creative design concepts. This model; outperforms the classical idea generation process in terms of innovation, number, and variety. However, more data is needed to comment on the functional properties of the generated concepts. The effect of the proposed model on function and aesthetics can be revealed by detailed evaluation. Therefore, more than this may be required for complex engineering design problems.

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REFERENCES

1. Börklü, H. R., Yüksel, N., Çavdar, K. and Sezer, H. K. "A practical application for machine design education", Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol. 12, Issue 2, 2018.

2. Yüksel N. and Börklü, H. R., "Yapay Zekâ Destekli Kavramsal Tasarım: Tekerlekli Sandalye Tasarım Seçenekleri Değerlendirmede Bulanık Mantık Kullanımı," Gazi Journal of Engineering Sciences, Vol. 7, Pages 309-316, 2021.

3. Huang, Y., Li, J. and Fu, J., "Review on Application of Artificial Intelligence in Civil Engineering", Computer Modeling in Engineering \& Sciences, Vol. 121, Issue 3, Pages 845-875, 2019. [Online]. Available: http://www.techscience.com/CMES/v121n3/38073

4. Han, J., Shi, F., Chen, L. and Childs, P. R. N. "The Combinator – a computer-based tool for creative idea generation based on a simulation approach", Design Science, Vol. 4, Pages e11, 2018.

5. Vasconcelos L. A. and Crilly, N., "Inspiration and fixation: Questions, methods, findings, and challenges," Design Studies, Vol. 42, Pages 1-32, 2016/01/01/ 2016.

6. Jansson, D. G. and Smith, S. M., "Design fixation", Design Studies, Vol. 12, Issue. 1, Pages 3-11, 1991.

7. Goldschmidt, G. and Smolkov, M., "Variances in the impact of visual stimuli on design problem solving performance", Design Studies, Vol. 27, Issue 5, Pages 549-569, 2006.

8. Goldschmidt, G. and Sever, A. L., "Inspiring design ideas with texts", Design Studies, Vol. 32, Issue 2, Pages 139-155, 2011.

9. Jiang, S. Luo, J., Ruiz-Pava, G., Hu, J. and Magee, C. L., "Deriving Design Feature Vectors for Patent Images Using Convolutional Neural Networks", Journal of Mechanical Design, Vol. 143, Issue 6, 2021.

10. Liu, Q., Wang, K., Li, Y. and Liu, Y., "Data-Driven Concept Network for Inspiring Designers' Idea Generation", Journal of Computing and Information Science in Engineering, Vol. 20, Issue 3, 2020.

11. Boden, M. A., "The Creative Mind: Myths and Mechanisms", London, UK: Routledge, 2004.

12. Ward, T. B., and Kolomyts, Y., "Cognition and Creativity," in The Cambridge Handbook of Creativity, J. C. Kaufman and R. J. Sternberg Eds., Cambridge Handbooks in Psychology. Cambridge: Cambridge University Press, Pages 93-112, 2010.

13. Jin, X., and Dong, H., "New desıgn heurıstıcs ın the dıgıtal era," Proceedings of the Design Society: DESIGN Conference, Vol. 1, Pages 607-616, 2020.

14. Yilmaz, S., Daly, S. R. Seifert, C. M. and Gonzalez, R., "Evidence-based design heuristics for idea generation", Design Studies, Vol. 46, Pages 95-124, 2016.

15. Shi, F., Chen, L., Han, J. and hilds, P. C., "A Data-Driven Text Mining and Semantic Network

Analysis for Design Information Retrieval", Journal of Mechanical Design, Vol. 139, Issue 11, 2017.

16. Bell, S. and Bala, K., "Learning visual similarity for product design with convolutional neural networks", ACM Transactions on Graphics, Vol. 34, Pages 98:1-98:10, 2015.

17. Yu, S., Dong, H., Wang, P., Wu, C., and Guo, Y., "Generative Creativity: Adversarial Learning for Bionic Design", Cham, 2019: Springer International Publishing, in Artificial Neural Networks and Machine Learning – ICANN 2019: Image Processing, Pages 525-536, 2019.

18. Chen, L. et al., "An artificial intelligence based data-driven approach for design ideation", Journal of Visual Communication and Image Representation, Vol. 61, Pages. 10-22, 2019.

19. Salehi, H. and Burgueño, R., "Emerging artificial intelligence methods in structural engineering," Engineering Structures, Vol. 171, Pages 170-189, 2018.

20. Alpaydın, E., Dietterich, T., "Ed. Introduction to Machine Learning", 3 ed. London: MIT Press, 2014.

21. Rebala, G., Ravi, A., and Churiwala, S., "An Introduction to Machine Learning", 1 ed. Cham: Springer, 2019.

22. Houssein, E. H., Emam, M. M., Ali, A. A. and Suganthan, P. N. "Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review", Expert Systems with Applications, Vol. 167, Page 114161, 2021.

23. Gal, Y. "Uncertainty in Deep Learning", PhD thesis, Department of Engineering, University of Cambridge, Cambridge, 2016.

24. Oh, S., Jung, Y. Kim, S., Lee, I., and Kang, N., "Deep generative design: Integration of topology optimization and generative models", Journal of Mechanical Design, Vol. 141, Issue 11, 2019.

25. Singh, R. D., Mittal, A. and Bhatia, R. K., "3D convolutional neural network for object recognition: a review", Multimedia Tools and Applications, Vol. 78, Issue 12, Pages 15951-15995, 2019.

26. Yi, X. Walia, E. and Babyn, P. "Generative adversarial network in medical imaging: A review", Medical Image Analysis, Vol. 58, Page 101552, 2019.

27. Jin, L., Tan, F. and Jiang, S., "Generative Adversarial Network Technologies and Applications in Computer Vision", Computational Intelligence and Neuroscience, Vol. 2020, Page 1459107, 2020.

28. Rahman, R., "Using Generative Adversarial Networks for Content Generation in Games", MSc thesis, Departman of Computer Games Technology, Abertay University, Dundee, 2020.

29. Ray, S. "A Quick Review of Machine Learning Algorithms," in 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 14-16 Feb. 2019. Pages 35-39,

30. Brynjolfsson, E. and Mitchell, T., "What can machine learning do? Workforce implications", Science, Vol. 358, Issue 6370, Pages 1530, 2017.

31. Mayda, M. and Börklü, H. "Yeni bir kavramsal tasarım işlem modeli", TÜBAV Bilim Dergisi, Vol. 1, Issue 1, Pages 13-25, 2008.

32. Börklü, H. "Computer-aided conceptual design based on design catalogues", Politeknik Dergisi, Vol. 4, Issue 3, Pages. 77-78, 2001.

33. Koestler, A., "The Act of Creation", Macmillan, Oxford, England, 1964.

34. Yi, X., Walia, E., and Babyn, P., "Generative adversarial network in medical imaging: A review", Medical Image Analysis, Vol. 58, Page 101552, 2019.

35. Jin, L., Tan F. and Jiang, S., "Generative Adversarial Network Technologies and Applications in Computer Vision", Computational Intelligence and Neuroscience, Vol. 2020, Pages 1459107, 2020.

36. Rahman, R., "Using Generative Adversarial Networks for Content Generation in Games," Thesis, School of Design and Informatics, Abertay University, 2020.

37. Oh, S., Jung, Y., Kim, S. Lee, I. and Kang, N. "Deep generative design: Integration of topology optimization and generative models," Journal of Mechanical Design, Vol. 141, Issue 11, 2019.

38. 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, Montréal, Canada, Dec. 8–13, Pages 2672–2680, 2014.

39. Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B. And Bharath, A. A. "Generative Adversarial Networks: An Overview,"

IEEE Signal Processing Magazine, Vol. 35, Issue 1, Pages 53-65, 2018.

40. Fang, W., Zhang, F., Sheng, V. S., and Ding, Y. “A method for improving CNN-based image recognition using DCGAN,” Computers, Materials and Continua, Vol. 57, Issue 1, Pages 167-178, 2018.

41. Yüksel, N., Börklü, H. R., Sezer, H. K. and Canyurt, O. E. (2023). Review of artificial intelligence applications in engineering design perspective. Engineering Applications of Artificial Intelligence, Vol. 118, Pages 105697, 2023.

42. Daly, S. R., Seifert, C. M., Yilmaz, S. and Gonzalez, R., "Comparing Ideation Techniques for Beginning Designers." ASME. Journal of Mechanical Design, Vol. 138, Issue 10, Pages 101108, 2016.