GEN AI-DRIVEN ELECTRONICS: INNOVATIONS, CHALLENGES AND FUTURE PROSPECTS

Conference Paper · November 2023

DOI: 10.5281/zenodo.8165255

1 author:

Archana Yadav
Gujarat Technological University

GEN AI-DRIVEN ELECTRONICS: INNOVATIONS, CHALLENGES AND FUTURE PROSPECTS

Archana Balkrishna Yadav
Independent Researcher, Vadodara, Gujarat, India

Abstract: The capacity of artificial intelligence (AI) to provide innovative and realistic outcomes has led to its rise in popularity. With programmes like ChatGPT1, Dall-E2, and Midjourney3 giving consumers access to Large Language Models (LLMs), generative artificial intelligence, or GenAI, has expanded quickly. On the other hand, a lack of a widely recognised definition for GenAI may cause misconceptions. Generative models are more complex algorithms that can generate high-quality, human-like material. Examples of these models include Variational Autoencoders (VAE) and Generative Adversarial Networks (GANs). Gen-AI is the term used to describe the combination of artificial intelligence (AI) and genetic algorithms in the electronics sector. This has resulted in a number of applications, including electronic circuit optimisation, improved hardware design and evolution, self-learning and adaptation facilitation, improved fault tolerance and self-repair, designing and controlling evolutionary robotics, and optimising co-design of hardware and software, evolutionary manufacturing, and electronic design automation. AI-driven chip design, genetic algorithms in circuit design, hardware optimised for AI, self-repairing circuits, autonomous electronics manufacturing, AI-enhanced Internet of Things devices, neuromorphic computing, and robotic evolution are some of the innovations in Gen-AI electronics. Four major obstacles stand in the way of Gen-AI, though: inaccurate outcomes, prejudice and fairness, infringement on intellectual property, and environmental issues. In the future, Gen AI will be utilised in the electronics industry to optimise the following: adaptive hardware-software co-design, real-time resource management, embedded systems and evolutionary robotics, energy-efficient hardware design, automated circuit design, self-healing electronics, real-time resource management, adaptive hardware-software co-design, and ethical and sustainable electronics design.

1. INTRODUCTION

Artificial Intelligence (AI) has become a fascinating subject that interests academics, business professionals, and members of the public in equal measure. Its ability to generate imaginative and realistic results, coupled with its accessibility, may be the reason for its rising popularity. These factors have far-reaching effects on a variety of fields, including software development [12], [13], marketing [10], [11], art [6], [7], music [8], [9], and medicine [1-3]. While artificial intelligence (AI) has gained popularity recently, the area of generative artificial intelligence, or GenAI, has grown explosively in the last few months of 2022 [14]. A significant advancement in the application of artificial intelligence to content generation has been made possible by the release of apps like ChatGPT1, Dall-E2, and Midjourney3, which provide end users with access to Large Language Models (LLMs) [15], [16]. These apps allow a broad range of users to easily create texts that resemble humans, realistic images, and even music [17]. However, when we talk about GenAI, what do we really mean? What kinds of content were being produced before commercial programmes such as ChatGPT were available? And why? It's important to grasp the exact definition and use of generative AI before delving into its intricacies. You should also have a closer look at the content creation procedures that were in place before these methods were placed in the hands of customers. We can learn more about the underlying goals and reasons for the use of generative AI solutions by looking at these variables. Examining the nomenclature in more detail, the definition of "generative" is "(being) able to produce or create something." According to this definition, all artificial intelligence models are generative in theory as they are always able to "produce or create something," whether it be internal rules or numerical predictions. But not every AI-powered content creation is or has ever been regarded as generative AI. Actually, depending on the data they were trained on, models that have the potential to generate new, never-before-seen knowledge have been more accurately referred to as "generative AI" models. Rather than only providing internal rules or numerical predictions, these models are producing new, human-like content that can be interacted with and consumed.

The absence of a well accepted definition for "Generative AI" may lead to confusion and misunderstandings. As previously indicated, some might argue that a straightforward decision tree model that generates rules based on incoming input is an example of generative artificial intelligence. However, unlike discriminative models (such decision tree models), which are taught to predict probabilities of labels given data, the AI research community reserves the word "generative" for more sophisticated algorithms that can produce high-quality, human-like content [18]. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAE) are two instances of the so-called generative models [19] (Fig. 1).

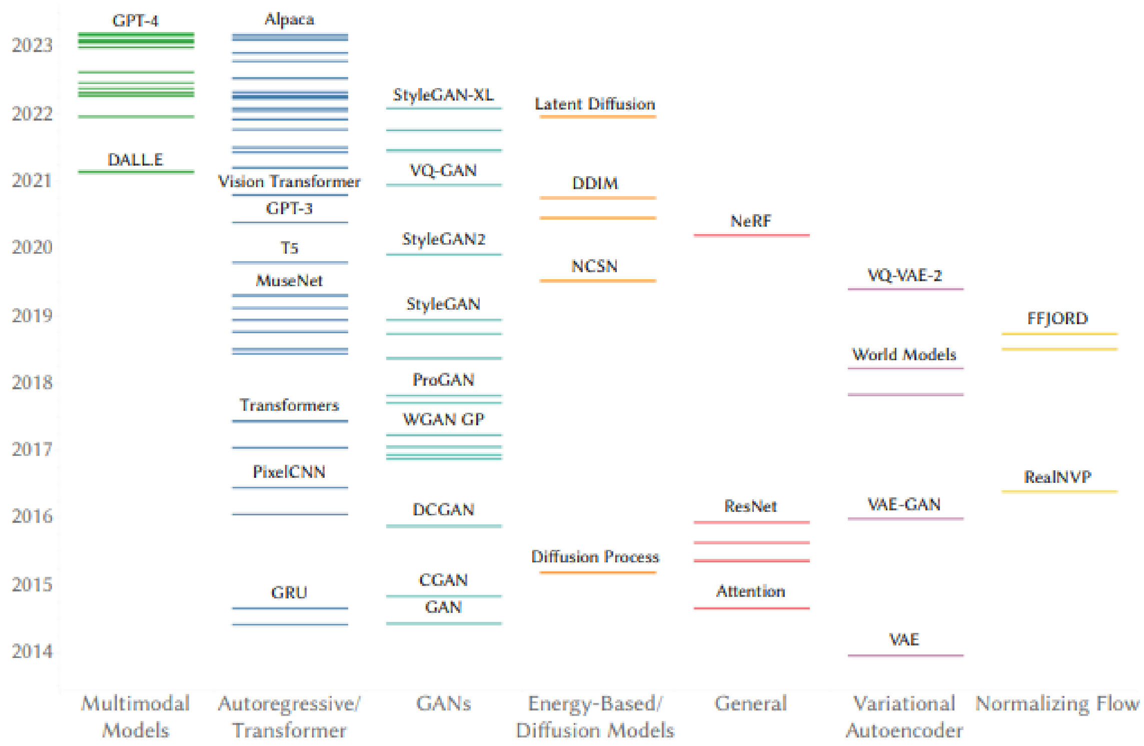

Figure 1: Timeline of generative models by type. Elaborated by the authors. Source data from [20]. High-resolution version available at https://doi. org/10.5281/zenodo.8165255.

But are generative models limited to using these types of models, even if their internal workings and the probabilities they estimate have previously allowed generative models to be distinguished from discriminative models [19]? Do the fundamental features of the model matter when confirming that material was created using generative AI? Or do the material's characteristics and the end goal take precedence?

Without a precise definition, scholars can refer to different content generation techniques as "generative AI," which might cause misunderstandings. This may hinder future study on the topic and make it difficult to compare and contrast different findings.

Additionally, this ambiguity may make it difficult for the general public and industry professionals to understand what generative AI is and what it can do, which might result in inflated expectations or concerns about its potential and hinder the adoption and acceptance of this technology.

The purpose of this study is to better clarify and delineate the meaning and use cases of Generative AI by offering an examination of AI-driven content generating solutions. A methodical approach—more precisely, a systematic mapping of the literature—was used to conduct this study [21]. In the rapidly developing area of generative artificial intelligence, a systematic mapping offers an organised framework for analysing the body of research, identifying trends, and pointing out any gaps. It emphasises the breadth of the topic rather than its depth, which is vital in fields that are developing quickly. This procedure helps to create a uniform discourse, reduce uncertainty, and define precise definitions and limits within the area.

II. RELATED WORK

There are many uses for generative AI in electronics. In order to help train machine learning models with minimal training data, it may be used to create fake data for circuit design [22]. By using the underlying physics of newly developed devices, generative AI may also be utilised to create probabilistic neural circuits for random number creation [23]. Generative artificial intelligence (AI) has the potential to enhance PCB production quality by identifying and locating manufacturing faults [24]. Furthermore, artificial electroencephalography (EEG) signals generated by generative deep learning have shown promise for use in neural engineering applications [25]. These illustrations show how versatile generative AI is in the electronics domain, facilitating improvements in defect detection, random number generation, circuit design, and EEG signal synthesis.

In the offered study, it is discussed how to increase the accuracy of machine learning models trained with sparse data by using generative adversarial networks (GANs) to create synthetic data for circuit design [22]. The use of generative AI in electronics is not particularly discussed in the article that is supplied [23]. The use of generative AI in electronics is not discussed in detail in the study. In-depth information on generative AI's history, varieties, uses, and efforts in Korea and the international market are included in this study [24].

In the offered research, it is suggested to use Generative Adversarial Networks (GANs) for printed circuit board (PCB) manufacturing fault identification [25]. The use of generative AI in electronics is not covered in the paper that is supplied. It focuses on creating artificial electroencephalography (EEG) signals using neural engineering and generative deep learning [26].

III. GEN-AI IN ELECTRONICS

The term "Gen-AI" may be used to describe the fusion of artificial intelligence (AI) with genetic algorithms (Gen) in the electronics industry. Here are a few possible uses and advancements in this field:
Optimisation of Electronic Circuits: The architecture and design of electronic circuits may be made more efficient by using genetic algorithms. Genetic algorithms repeatedly adapt circuit designs to satisfy predetermined requirements, including performance, power consumption, or size, by mimicking the process of natural selection.

Hardware Design and Evolution: AI methods in conjunction with genetic algorithms may help with hardware architecture design and evolution. This involves enhancing the functionality, dependability, and energy efficiency of microprocessors, memory systems, and other electronic components by structural optimisation.

Artificial Intelligence (AI) algorithms have the potential to be incorporated into electronic systems to facilitate self-learning and adaption. Through the use of genetic algorithms, learning may be optimised, enabling electronic devices to gradually enhance their usefulness and performance.

Fault Tolerance and Self-Repair: Artificial intelligence (AI) and genetic algorithms may help electronic systems recognise and fix problems on their own. These systems are capable of identifying problems and rearranging themselves to avoid or fix broken components, increasing dependability and uptime, by evaluating sensor data and system behaviour.

Evolutionary Robotics: Robotics and autonomous systems may be designed and controlled via the use of genetic algorithms and artificial intelligence approaches. Robot morphologies and control tactics are changing to enable these systems to adapt to varying tasks and situations, resulting in more robust and flexible robotic platforms.

Co-design of Hardware and Software: Artificial Intelligence and Genetic Algorithms may help optimise the co-design of Hardware and Software components in Electronic Systems. Improved performance, energy efficiency, and scalability may be attained by designers via the simultaneous optimisation of software algorithms and hardware architecture.

Evolutionary Manufacturing Optimisation: The production processes of electronic devices and components may be made more efficient via the use of AI and genetic algorithms. To increase productivity and save expenses, this entails optimising production scheduling, resource allocation, and quality control.

AI-Driven Electronic Design Automation (EDA): AI and genetic algorithms may improve semiconductor industry-used electronic design automation systems. Through the automation of processes like timing analysis, layout synthesis, and verification, these technologies may expedite the design process and enhance the overall quality of the design.

These are just a few instances of how artificial intelligence and genetic algorithms are fostering innovation in the electronics industry. We may anticipate further integration of these approaches to revolutionise electronic design, manufacture, and operation as technology progresses.

IV. INNOVATIONS IN GEN-AI ELECTRONICS

"Gen-AI electronics" doesn't relate to a particular phrase or technology in the industry as of my most recent update in January 2022. However, there may be a few improvements to look into if you're talking about advances in electronics powered by genetic algorithms and artificial intelligence (AI/Genetic AI):

AI-Driven Chip Design: Businesses are using AI algorithms more often to create computer chips that are more potent and efficient. AI can enhance performance, save power usage, and optimise chip architecture.

Using Genetic Algorithms in Circuit Design: Circuit designs may be optimised via the application of genetic algorithms. Genetic algorithms create more inventive and efficient electrical systems by evolving and improving circuit designs via several generations, akin to the process of natural selection.

AI-Optimized Hardware: The hardware architecture itself may be made more efficient by using AI algorithms. This involves creating hardware accelerators, such neural processing units (NPUs) or tensor processing units (TPUs), specifically for AI workloads.

Self-Repairing Circuits: Self-repairing circuits may be made possible by combining genetic and artificial intelligence techniques. The dependability and lifespan of electronic systems are increased by these circuits' capacity to recognise problems or mistakes and adjust their own configuration to avoid or replace the harmed parts.

Autonomous Electronics Manufacturing: Genetic algorithms and AI-powered robots can streamline the production of electrical gadgets and components. This covers predictive maintenance, automated quality control, and adaptive manufacturing techniques that can make real-time adjustments in response to changes in the material's qualities or the environment.

AI-Enhanced IoT Devices: Artificial intelligence (AI) algorithms may be used to Internet of Things (IoT) devices to increase their usefulness, security, and energy efficiency. In order to ensure optimum performance and resource utilisation, genetic algorithms may optimise the deployment and operation of Internet of Things networks.

Neuromorphic computing: Using genetic and artificial intelligence techniques, neuromorphic computing creates hardware designs that emulate the brain's parallel processing capabilities. It is inspired by the structure and operation of the human brain. These systems have the potential to provide computer platforms for AI applications that are more potent and efficient.

Robotic Evolution: Genetic algorithms may be used to robotics to develop control algorithms and robot designs. Robots can adapt and learn in dynamic, complicated situations thanks to this technique, which creates robotic systems that are more robust and adaptable.

These are just a few instances of how artificial intelligence and genetic algorithms are fostering innovation in the electronics industry. We may anticipate further AI and genetic algorithm integration to completely transform electronic design, production, and operation as technology develops.

V. CHALLENGES AND LIMITATIONS

The following highlights four key generative AI limits that, in our opinion, represent significant restrictions for practical use. The following restrictions are of a technical nature as they speak to the way that existing generative AI models draw conclusions; as such, they are model-specific. This means that long-term limits are likely to exist, with repercussions at the system and application levels.

Erroneous Results

Models using generative AI may provide incorrect results. This might be attributed to the fundamental characteristics of machine learning models, which depend on probabilistic methods to draw conclusions. Generative AI models, for instance, provide the most likely answer to a query, not always the right one. Consequently, difficulties emerge since outputs may now be mistaken for real material and may mislead or fool people. This emergent behaviour issue in LLMs is referred to as "hallucination," which describes errors in the produced text that are accurate or nonsensical but are reasonable from a semantic or syntactic standpoint. Put differently, the generative AI model generates material based not on any evidence or facts, but rather on its own presumptions or prejudices. Furthermore, generative AI's output—particularly that of LLMs—is sometimes difficult to verify.

The quality of training data and the corresponding learning process have a significant impact on how accurate generative AI models are. Correctness checks may be used by generative AI systems and applications to prevent certain outputs. But since modern AI models are opaque, users' confidence in the systems' ability to provide accurate results is crucial to their use. This reality is exacerbated by the closed source nature of commercial off-the-shelf generative AI systems, which prevents further model adjustment and retraining. Using generative AI to provide justifications or references that users may verify is one way to alleviate the downstream effects of inaccurate outputs. Though these justifications are also probabilistic and prone to inaccuracies, they might nonetheless assist users in determining whether and not to accept generative AI results.

Fairness and Bias

Everyday human-generated material is infused with societal prejudices. Vanilla generative AI's objectivity is heavily reliant on the calibre of the alignment procedure and training data. Deep learning algorithms trained on skewed data have the potential to reinforce negative language, magnify human prejudices, and maintain gender, sexual orientation, political leaning, and religious stereotypes. The detrimental biases present in multimodal generative AI models, such Dall-E 2 or Stable Diffusion, have been made clear by recent work using CLIP and the CLIP-filtered LAION dataset. In various phases of the model-engineering process, human biases may also find their way into the models. The RLHF procedure is an additional source of bias for instruction-based language models (OpenAI 2023b). Strict coding standards and quality assurance procedures may aid in reducing these hazards.

Although it is still an open research subject, addressing prejudice and hence fairness in AI is receiving more attention in the academic literature. For instance, "probing and understanding the limitations and biases of generative models" is highlighted as a crucial study field by the creators of Stable Diffusion. According to some academics, models have the ability to self-correct morally, which may lessen worries about ingrained prejudices and promote justice. Furthermore, mitigation strategies may be used at the system and application level to remove biases present in the deep learning models and provide outputs that are more varied. However, additional investigation is required to approach the concept of equitable AI.

Infringement of Copyright

Because generative AI models, systems, and apps may generate outputs that mimic or even replicate existing works without the permission or payment of the original authors, they may violate copyright laws. There are two common possible infringement hazards here. Generative AI has the potential to infringe upon authors' rights to reproduction by producing illicit copies of works. This may occur, among other things, if a generative AI was educated on copyright-protected original material and then creates duplicates of it. Therefore, a common inference is that copyrights must not be included in the training data used to create generative AI systems. Importantly, copyright infringement may still occur even in cases where the generative AI has never seen a copyrighted work before. An example of this would be if the AI just creates a trademarked logo that resembles Adidas' emblem without ever having seen it before. However, generative AI has the potential to produce derivative works, infringing upon artists' rights to transformation. As a result, the balance between originality and creativity in generative AI systems gives rise to legal concerns. In keeping with this, legal issues also surface around who owns the intellectual property for works (including patents) generated by generative artificial intelligence.

Environmental Issues

Last but not least, the development and application of generative AI systems raises serious environmental issues because they are usually based on large-scale neural networks, which have a significant negative carbon footprint during development and operation. Because of this, attempts are being made in AI research to build and implement AI algorithms in a way that is less harmful to the environment via the use of more effective training algorithms, smaller neural network topologies, and better hardware.

VI. FUTURE RECOMMENDATION

Of course! The following are some suggestions for the future use of Gen AI, or artificial intelligence plus genetic algorithms, in the electronics industry:

Optimising Automated Circuit Design: Create general artificial intelligence (Gen AI) algorithms that can automate the design and optimisation of electrical circuits while taking manufacturability, performance, power consumption, and area into account. This entails combining AI methods with genetic algorithms to effectively explore the large design space and provide excellent circuit designs.

Self-Healing Electronics: Examine how Gen AI may be used to develop self-healing electrical systems that can identify and fix problems on their own. Artificial Intelligence (AI) approaches may facilitate real-time monitoring and decision-making to guarantee the lifetime and dependability of electronic systems, while genetic algorithms can be used to develop problem detection and repair solutions.

Energy-Efficient Hardware Design: Create Gen AI techniques to optimise electrical device hardware architecture for maximum energy efficiency. This entails using AI approaches to precisely forecast energy usage and performance trade-offs, as well as genetic algorithms to investigate various design configurations.

Embedded systems and evolutionary robotics: Use Gen AI methods in embedded system and robotics design and optimisation. Robot morphologies, control algorithms, and embedded hardware configurations may all be evolved using genetic algorithms to increase resilience, performance, and flexibility in a variety of applications.

Multi-Objective Optimisation in Electronics Manufacturing: Create Gen AI systems that can optimise many goals at once in the processes involved in making electronics. This entails applying genetic algorithms and AI-based decision-making to optimise production results by taking into account variables like cost, yield, cycle time, and

Resource Utilisation

Examine Gen AI techniques for adaptive hardware-software co-design in electronic systems under the heading of adaptive hardware-software co-design. Co-evolution of software algorithms and hardware designs using genetic algorithms may maximise system performance, energy efficiency, and resource utilisation.

The goal of this project is to create Gen AI algorithms for real-time resource management in edge computing systems and IoT devices. This entails employing genetic algorithms and AI-based predictive analytics to dynamically allocate compute resources, bandwidth, and energy depending on shifting workload needs and environmental circumstances.

Bio-Inspired Electronics Design: Using Gen AI methods, investigate bio-inspired ideas for electronics design. Neural networks, genetic circuits, and swarm intelligence-based architectures are examples of creative electronic designs that are influenced by biological systems. Genetic algorithms may replicate the evolutionary processes seen in nature.

Ethical and Sustainable Electronics Design: Apply Gen AI techniques to ethical and sustainable electronics design issues. This entails applying social responsibility, resource efficiency, and environmental impact limitations to the optimisation process via the use of AI-based decision-making and genetic algorithms.

Collaborative AI platforms for electronics design and optimisation should be created in order to facilitate information sharing, idea exchange, and teamwork among researchers, engineers, and domain specialists in the resolution of challenging electronics optimisation challenges. Researchers and practitioners may use the potential of Gen AI to promote innovation, efficiency, and sustainability in the design, production, and operation of electronic systems by following these future guidelines.

VII. CONCLUSIONS

In summary, the use of Gen AI in electronics has great potential to promote sustainability, efficiency, and creativity in a variety of fields. Gen AI provides a potent framework for addressing challenging optimisation issues in electronics design, production, and operation by combining the enormous solution space exploration capabilities of genetic algorithms with the intelligent decision-making capabilities of AI approaches.

Automated circuit design optimisation, self-healing electronics, energy-efficient hardware design, evolutionary robotics and embedded systems, multi-objective manufacturing optimisation, adaptive hardware-software co-design, real-time resource management in Internet of Things devices, bio-inspired electronics design, and ethical and sustainable electronics design are some of the key areas where Gen AI is poised to make significant contributions in the electronics field.

Researchers and practitioners may open up new avenues for developing inventive electronic systems that are more dependable, effective, and flexible to changing conditions and demands by using Gen AI approaches. Additionally, Gen AI makes it possible to create cooperative optimisation platforms that promote expert cooperation and knowledge exchange, resulting in quicker and more efficient solutions to real-world electronics problems.

All things considered, Gen AI heralds a prospective paradigm change in electronics by providing fresh methods for taking on challenging optimisation challenges and propelling progress across a range of application areas. We may anticipate seeing more advanced and revolutionary applications that completely alter the way electronic systems are created, built, and used as Gen AI research and development continues to advance.

REFERENCES

1. J.-M. Flores-Vivar and F.-J. García-Peñalvo, “Reflections on the ethics, potential, and challenges of artificial intelligence in the framework of quality education (SDG4),” Comunicar, vol. 31, no. 74, pp. 37-47, 2023.
2. H. Khosravi et al., “Explainable artificial intelligence in education,” Computers and Education: Artificial Intelligence, vol. 3, p. 100074, 2022.
3. A. Chatterjee, “Art in an age of artificial intelligence,” Frontiers in Psychology, vol. 13, p. 1024449, 2022.
4. B. Agüera y Arcas, “Art in the age of machine intelligence,” in Arts, 2017, vol. 6, no. 4, p. 18: MDPI.
5. M. Civit, J. Civit-Masot, F. Cuadrado, and M. J. Escalona, “A systematic review of artificial intelligence-based music generation: Scope, applications, and future trends,” Expert Systems with Applications, p. 118190, 2022.
6. J. Lies, “Marketing Intelligence: Boom or Bust of Service Marketing?,” International Journal of Interactive Multimedia and Artificial Intelligence, vol. 7, no. 7, pp. 115-124, 2022.
7. R. H. Kulkarni and P. Padmanabham, “Integration of artificial intelligence activities in software development processes and measuring effectiveness of integration,” IET Software, vol. 11, no. 1, pp. 18-26, 2017.
8. A. Mashkoor, T. Menzies, A. Egyed, and R. Ramler, “Artificial intelligence and software engineering: Are we ready?,” Computer, vol. 55, no. 3, pp. 24-28, 2022.
9. T. van der Zant, M. Kouw, and L. Schomaker, “Generative Artificial Intelligence,” in Philosophy and Theory of Artificial Intelligence, V. C. Müller, Ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 107- 120.
10. J. Yang et al., “Harnessing the power of llms in practice: A survey on chatgpt and beyond,” arXiv preprint arXiv:2304.13712, 2023.

11. F. J. García-Peñalvo, "The perception of Artificial Intelligence in educational contexts after the launch of ChatGPT: Disruption or Panic?," Education in the Knowledge Society, vol. 24, art. e31279, 2023.
12. D. Foster, "Generative deep learning: teaching machines to paint," Write, Compose, and Play (Japanese Version) O'Reilly Media Incorporated, pp. 139-140, 2019.
13. H. Gm, M. K. Gourisaria, M. Pandey, and S. S. Rautaray, "A comprehensive survey and analysis of generative models in machine learning," Computer Science Review, vol. 38, p. 100285, 2020/11/01/ 2020.
14. D. Foster. (2023). Generative Deep Learning - 2nd Edition Codebase. Available: https://github.com/davidADSP/Generative_Deep_ Learning_2nd_Edition/tree/main
15. F. J. García-Peñalvo, "Developing robust state-of-the-art reports: Systematic Literature Reviews," Education in the Knowledge Society, vol. 23, p. e28600, 2022.
16. (2023). Qualitative Data Augmentation for Performance Prediction in VLSI circuits. doi: 10.48550/arxiv.2302.07566
17. Bokuan, Yang., Yuhu, Nie., Wenpeng, Cui., Jian, Sun., Hao, Lu., Wei, Su. (2022). Generative adversarial network for PCB defect detection with extreme low compress rate. doi: 10.1117/12.2660551
18. Ozan, Ozdenizci., Deniz, Erdogmus. (2021). On the use of generative deep neural networks to synthesize artificial multichannel EEG signals. doi: 10.1109/NER49283.2021.9441381