Materials Today Electronics 11 (2025) 100136

Contents lists available at ScienceDirect

Materials Today Electronics

journal homepage: www.elsevier.com/locate/mtelec

Review

Overview of emerging electronics technologies for artificial intelligence: A review

Peng Gao [a], Muhammad Adnan [b,c,*]

[a] Communication and Information Engineering, Chongqing College of Mobile Communication, Chongqing 401520, PR China
[b] State Key Laboratory of Environmental Geochemistry, Institute of Geochemistry, Chinese Academy of Sciences, Guiyang, Guizhou 550081, PR China
[c] University of Chinese Academy of Sciences, Beijing 100049, PR China

ARTICLE INFO

Keywords:
Artificial intelligence
Deep learning
Electronics
Semiconductors
Robotics
Environmental challenges

ABSTRACT

This paper shows the short- and long-term electronics technologies emerging as the enablers of next-generation AI systems and focuses on rapidly developing technologies with promise toward enabling the new AI revolution, such as neuromorphic, quantum computing and edge AI processors. These technologies are key to improving the computational power, energy efficiency, and scalability required in AI solutions across healthcare, autonomous systems, and better endeavours. Neuromorphic computing works similarly to the brain's neural configuration to build a more energy-efficient AI system by simulating biological functionality, while quantum computing is ubiquitous as the next stage of problem-solving systems in AI and exponentially increases computational speed and functionality. Finally, Edge AI processors play an important role in real-time AI decision-making, especially in environments with limited power and space, as they allow data to be processed at the original point of generation. Of course, although these technologies demonstrate great potential, there are still obstacles to overcome for subtle hardware-software integration, architecture scalability and high energy consumption. This study highlights sustainable hardware design as an essential solution to these challenges, discussing low-power chips, AI accelerators and energy-efficient designs that allow devices to run at scale without performance liabilities. The paper also highlights quantum and neuromorphic computing—which mimics the structure and function of biological brains—as an important focus for overcoming limitations regarding scalability, allowing for novel architectures equipped to deal with the extremely large amounts of data required for future, more advanced AI models. We also discuss how these progressions can facilitate the creation of effective and scalable AI systems that support AI in addressing global challenges like environmental deterioration and resource limitations. Lastly, the paper highlights the importance of ongoing research and innovation in such areas to promote the evolution of AI systems that are resilient, scalable and energy-efficient in a way that ensures the long-term sustainability of AI and its implementation in various domains.

1. Introduction

Electronics and artificial intelligence (AI) technology are advancing so rapidly that industries are continuously being reshaped while maximizing AI potential for decision-making, pattern recognition, etc., in their everyday life. This dataset expansion encourages innovation in the emerging fields of autonomous systems, machine learning (ML), and deep neural networks (DNNs) [1,2], leading to the convergence of AI with computing infrastructure. AI utilizes ML algorithms and intelligent medical robots to transform diagnostics, drug discovery, and patient care, enhancing diagnostic accuracy and surgical precision [3]. In finance, AI algorithms improve fraud detection, trading and risk assessment [2,4]. AI also significantly impacts the transportation sector, with applications in autonomous vehicles, traffic planning, and education through adaptive learning and personalized teaching [2,4]. Artificial Intelligence of Things (AIoT) meets the Internet of Things (IoT) to improve smart home automation, urban planning, and energy management, adding more AI to our daily life [1]. The combination of AI with the IoT for smart cities enables better urban planning, improvements to traffic management, and optimal energy consumption, resulting in more integrated and efficient environments [1]. With the rise of AI-driven applications in everyone's daily lives, the need to leverage

* Corresponding author at: State Key Laboratory of Environmental Geochemistry, Institute of Geochemistry, Chinese Academy of Sciences, Guiyang, Guizhou 550081, PR China.

E-mail address: adnan@mail.gyig.ac.cn (M. Adnan).

https://doi.org/10.1016/j.mtelec.2025.100136
Received 9 December 2024; Received in revised form 6 January 2025; Accepted 22 January 2025
Available online 23 January 2025

hardware/architecture solutions to cope with rising computational load is both critical and increasingly more demanding, ensuring that whilst we keep unlocking the true potential of AI technology, address the various ethical issues [5] and regulatory challenges. Wildly, this boosts innovation and growth across industries, changing how businesses operate, and societies interact to their core [5].

Advancements in hardware architectures are essential to help mitigate the challenges of AI systems that are both power-intensive and resource-greedy, making it clear that the evolution of AI and electronics has closely followed advances in hardware architectures. With AI in electronics, design processes become more efficient and innovative across industries [6]. Emerging computational paradigms like quantum computing, distributed systems, and neuromorphic computing provide prospective solutions to the optimization of AI algorithms, offering speedups that are exponential, scalable, and energy-efficient [7], including quantum computing, which exploits superposition and entanglement effects to perform certain types of computation faster. However, neuromorphic computing models the human brain's neural architecture to provide real-time, energy-efficient, high-speed processing [7]. The key lesson learned from AI history, which has atemporal implications, is that emerging technologies must be aligned with society and ethics [8]. Moreover, novel network architectures to mitigate bottlenecks in computing systems by increasing energy efficiency and adaptability are also presented, including embedded optical waveguides and wireless chip-to-chip links [9]. Overall, these changes indicate that the future landscape of AI will depend more on other types of hardware architecture as well as cross-disciplinary work that can guarantee that AI will be powerful and sustainable.

The significance of edge computing is growing and is becoming more and more important in facilitating real-time decision-making for various applications, such as autonomous vehicles, smart cities, and industrial IoTs, by allowing computation to be performed closer to the location where the data is generated, reducing latency and improving the responsiveness of the system. However, with the introduction of autonomous vehicles, communication, computation, and storage must be optimized in vehicular edge computing due to the low latency requirements of real-time applications. An innovative algorithm is proposed to decrease the service latency significantly (up to 64 %) through joint resource allocation as the data generated exponentially by these vehicles [10]. Such frameworks are needed to optimize AI/ML workloads, especially to improve resource allocation in edge environments, ultimately increasing resource utilization while minimizing latency [11]. Edge AI-augmented emphasizes processing data locally to reduce bandwidth requirements, provide the necessary privacy, and handle real-time intelligence needs for sectors such as manufacturing and healthcare [12]. For example, edge computing can greatly enhance data efficiency in smart cities by reducing transmission latency and alleviating network congestion, providing a sustainable urban management solution at the source level [13]. However, these improvements still have limited resources and security difficulties; research has begun on the new paradigm of neuromorphic computing, potential energy-efficient real-time computing, hardware, and other aspects to adapt to AI applications [12].

Considering the advantages of spiking neural networks (SNNs), such as biological plausibility and significantly reduced power consumption, many recent works on neuromorphic computing focus on improving the performance and scalability of neural network architectures, especially SNNs, compared to the traditional deep learning models [14,15]. The human brain is regarded as a nearby supercomputer in terms of tightly postulated SNNs for data processing, which is resource- and energy-efficient compared to a typical computer [16], such as parallelism, distribution, and event-driven processing [17]. Neuromorphic systems are designed to simulate the function of the brain using the material-neuron concept to mimic synaptic plasticity and cognitive functionalities indispensable for data processing and storage [18]. Moreover, the development of advanced materials such as porous crystalline materials and nanomaterials has also been a driving force towards the realization of flexible neuromorphic systems and the advancement of next-generation devices [18]. Hence, scaling traditional architectures poses challenges for large-scale applications, revealing their limitations being replaced by neuromorphic chips that promise to deliver parallelism, event-driven control, and adaptive learning [19] as a solution, showing a dramatic gain in performance and a significant gain in power efficiency. Furthermore, synchronization methods in an event-driven manner can improve the communication and computation performance of SNNs together, leading to orders of magnitude speedup compared to traditional simulators [15]. Furthermore, these innovations highlight the ability of neuromorphic computing to transform and its potential impact on the future of AI—opening new paths towards more cognition at scale.

Integrating renewable energy (RE) generators for smart grids is a complex process that can improve power distribution sustainability, flexibility, and efficiency. Smart grids combine modern technologies like AI, IoT and blockchain to maintain reliability and intelligence in energy management. AI contributes to achieving this goal by integrating advanced ML algorithms such as Linear Regression, Support Vector Regression and Long Short-Term Memory networks to develop predictive accuracy and optimize resource scheduling, leading to significant gains in energy efficiency and grid stability [20]. The implementation of both 6G IoT and AI also helps forecast grid load variation and regulate energy usage, especially during peak demand, to avoid overload and ensure a steady power delivery [21]. Moreover, blockchain technology improves transparency and trust in energy transactions, which is key for widely adopting renewable resources [21]. Smart grid operation relies on the synergy of electrical, control, and communication engineering, allowing RE sources such as solar and wind to penetrate the grid [22]. An example of the new features of smart grids is shown in (Fig. 1) [23]. This integration is aided by real-time data analytics and sophisticated communication technologies that optimize energy allocation and use, thus improving the stability and reliability of the electrical grid [24]. However, smart grids are an innovative approach to energy management, enabling increased penetration of RE sources and more sustainable development while minimizing their environmental impacts [20, 25].

The ability to solve certain problems more efficiently, or in a way not even conceivable classically, is becoming ever more apparent in the context of AI-enabled by quantum computing. This has great potential in AI implementations, including optimization, pattern matching, and data classification. Quantum algorithms, such as Shor's and Grover's, already showcase substantial advantages in specific areas, while recent developments address complex problems such as global optimization and data analysis [26]. Quantum-inspired algorithms like quantum annealing and the Quantum Approximate Optimization Algorithm (QAOA) support combinatorial optimization studies in AI and ML, improving data processing and pattern recognition abilities [27]. Quantum Artificial Intelligence (QAI) seeks to combine AIs with quantum computing to create more advanced computational techniques, employing qubits to store information and execute computations significantly quicker than traditional computers [28]. Quantum machine learning (QML) aims to bypass barriers of classical ML by exploiting quantum phenomena, such as superposition and entanglement, enabling algorithms like Quantum Support Vector Machines and Quantum Neural Networks to outperform classical counterparts for extensive datasets [29]. However, the implementation of QML is still limited by the state of the art in quantum technology [29]. Quantum neural networks (QNNs), specifically limited to those built by quantum optics, provide a thriving pathway in AI system development; however, complexities behind their implementation are still being tackled, and the pursuit of scaling them is ongoing [30]. Nevertheless, despite these challenges, quantum computing is still a promising path forward for improving AI systems, especially with highly complex tasks like drug discovery and climate modeling.

This review aims to illustrate that the continuous improvement of

Fig. 1. Major features of smart grids. Reprinted from [23], Copyright (2020), with permission from Publisher.

electronics has fueled real developments in AI technologies. Innovations in electronic hardware driving AI: the latest trends in semiconductors, specialized processors and energy-efficient systems. It will also explore the challenges and future exploration of electronics technology involved in AI evolution, showing solutions offered by new hardware architecture that an evolved AI requires to run efficiently and a device demanding

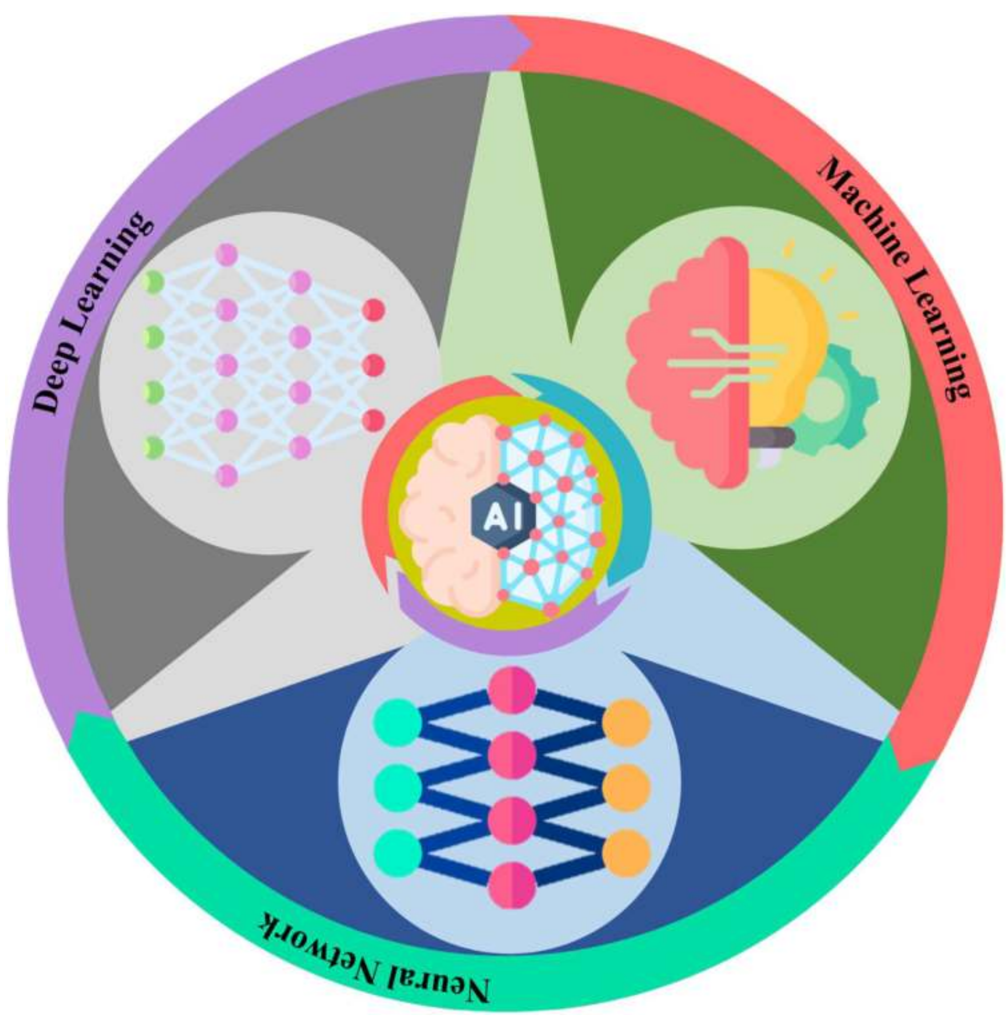

Fig. 2. Artificial intelligence and its fundamental type.

massive resources for its processing. This paper still aims to convey a sense of what technologies are helping AI become what we see now, the mixture between electronics and computer science, and the most precise way to elucidate inventions that are shaping the future and will forever change the world as we see it today.

2. Technologies and trends in electronics that enable AI

AI performance relies heavily on electronic technology. So, AI is subcategorized into three main types, as shown in Fig. 2. The identical structure of AI is based on neural networks, which is ML architecture that helps identify patterns and make predictions. A subfield of AI is ML, which is about creating algorithms that automatically learn to make decisions based on data rather than through explicitly coded rules, and it has been crucial for automating tasks across enterprises [31]. Fortunately, the emergence of deep learning, a subfield of ML, has provided a valuable improvement in this process by using deep neural networks (DNNs), which are multilayered neural networks to extract features from data that are too complex, thereby allowing AI to address complex tasks like image recognition and natural language processing with greater precision [32,33]. This progress across AI domains has been driven by substantial datasets and increased computational power, significantly influencing deep learning to enable further powerful applications such as predictive analytics, autonomous systems, and personalized healthcare solutions [32]. The developments from neural networks to deep learning would mean an advancement in the direction of powerful AI and are essential for creating super-intelligent machines that mimic human decision-making processes [33,34]. Growth is driven by deep learning, which requires the use of chips to handle computationally intensive tasks and to be processed in a cost-effective manner, such as dedicated chips (e.g. GPUs, TPUs). A step from these chips is improving AI system performance. Moreover, by optimizing neural networks' performance, accelerating energy efficiency, and protecting the neural networks, hardware acceleration is the key to Open AI and other ML innovations in all fields [35]. By optimizing algorithmic efficiency via techniques such as parallelization and minimax trees, further techniques support addressing computational complexity and scalability challenges that facilitate the deployment of AI models at scale [36]. Additionally, the convergence of AI with other cutting-edge technologies like quantum computing and blockchain is expected to create new possibilities for AI ventures, highlighting the importance of computational sustainability and energy efficiency [36]. Together, these technological innovations promote the development and implementation of AI, revolutionizing its use in various sectors, including healthcare, finance, and manufacturing, while also making AI more accessible and influential in day-to-day life.

2.1. Silicon growth and Moore's law

Hence, the recent chips and semiconductor technology boosted the advancement of AI, particularly through nanoelectronics and 3D chip architectures. These developments have led to the creation of processors that are smaller, quicker, and more efficient, all of which are necessary to manage the computational requirements of AI workloads like deep learning and neural networks. The scaling of smaller nodes like 5 nm and 3 nm processes will improve the performance and energy efficiency of AI hardware, following the trends outlined by Moore's Law, predicting a doubling of transistors on a chip approximately every two years [37,38]. Although silicon-based technology is physically limited, the semiconductor industry is still innovating by exploring alternative solutions such as system-in-package (SiP), chiplets, and quantum computing to maintain growth in computing performance [38,39]. So, based on its excellent performance, gallium nitride (GaN)-based devices should show better results than silicon carbon (SiC)-based devices [40]. As depicted in Fig. 3, silicon (Si) and wide-bandgap technologies (SiC, GaN) have different typical switching frequencies (x-axis) based on their power level (y-axis) [41]; however, the Si, silicon carbide (SiC), and gallium nitride (GaN) semiconductors offer unique advantages that prove beneficial for certain applications in the field of power electronics. As the most mature technology, Si is primarily employed in low-power applications, such as domestic devices, due to its low cost and well-known production processes [42]. Due to its superior properties of high thermal conductivity and high voltage and temperature operation, SiC benefits high-power applications, including EVs and wind turbines, which can present notable efficiency improvements [43]. Semiconductors are transforming the role played by AI, where the AI is refining chip design, manufacturing, and fault detection, which will take integrated circuits to a different level altogether [44,45]. Such a symbiosis between AI and semiconductor technologies is heralding a ``golden era'' of innovation, which in turn acts as a catalyzing factor for economic growth and productivity improvement in different sectors [37]. High-electron-mobility transistors (HEMTs) and other GaN-based devices exhibit low conduction losses and high efficiency, essential for miniaturized, efficient power converters [46,47]. The decision is

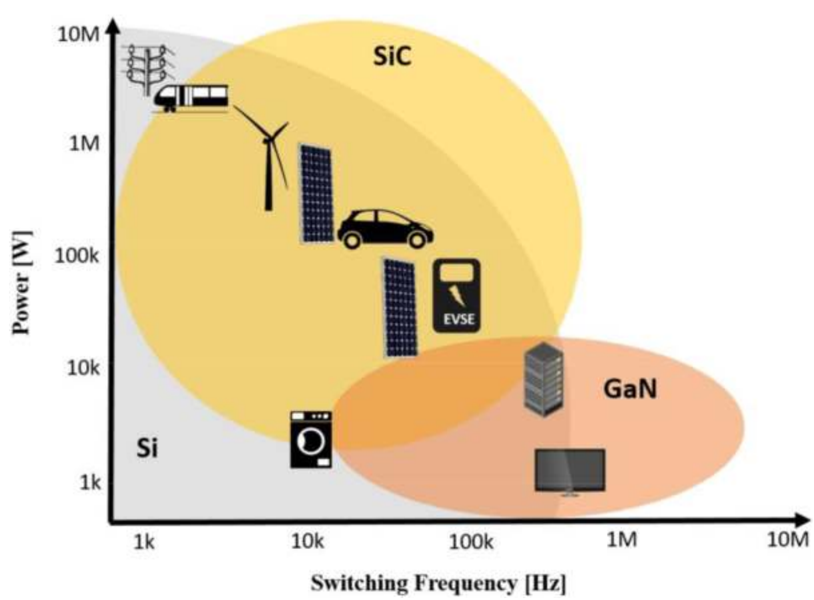

Fig. 3. Switching frequencies of Si, SiC and GaN technology. Reprinted from [41], Copyright (2022), with permission from Publisher.

generally based on the trade-offs outlined here, with each material providing advantages in different power, efficiency, and thermal requirements.

2.2. Graphics processing units (GPUs)

The introduction of GPUs laid the groundwork for this increasing evolution of AI implementations, as they provide parallel processing, which is invaluable when performing the large calculations needed for AI, especially to train deep learning models. While they were initially built to render graphics, GPUs have been modified to perform the high parallel processing that AI requires, making them orders of magnitude faster than general-purpose central processing units (CPUs) [48]. The critical role of GPUs, for instance, shows that efficient hardware acceleration is necessary to enhance performance, energy efficiency, and fault tolerance of neural networks for any task, such as high-speed train fault detection and isolation [35]. Moreover, the presence of GPUs in embedded applications, such as in neuromuscular devices, showcases their flexibility and the requirement to establish an appropriate hardware-software ecosystem to handle the elevated computational and memory requirements of neural networks with minimal energy consumption [49]. The accelerator paradigm in computer architecture is built around the combination of specialized processors connected to a host CPU that offloads appropriate computational kernels (Fig. 4), GPUs, AI accelerators, and quantum processing units (QPU) [50]. Unifying compute elements like CPUs, GPUs, AI accelerators, and QPUs into a system connected to a shared main memory is paramount in improving the performance of modern workloads, ranging from classical to AI inference and even quantum applications. GPU is suitable for parallel processing, which is required not only for graphics and simulations but also to speed up AI and ML because different algorithms are employed, providing relatively high computation speed [51,52]. Despite the many obstacles associated with power consumption and market monopolies, GPUs and other specialized chips, such as TPUs, continue to play an integral role in improving the performance of AI systems [53]. Along with other emerging accelerators with different designs, such as the Graphcore Intelligence Processing Unit (IPU) and Sambanova Reconfigurable Dataflow Unit (RDU), we can see hardware redesign for GPUs to keep up with the increasing complexity of AI/ML tasks [48]. On the other hand, teachers perform tasks using quantum algorithms on QPUs that can improve the ML process, potentially outperforming classical algorithms in certain areas [54]. An example of such integration is the quantum-classical-quantum (QCQ) architecture, which exploits the two contrasting resource types to circumvent obstacles associated with quantum simulations, yielding powerful computational advantages and high success rates for complex tasks [55]. This evolution is also supported by advanced design methodologies, e.g., the multi-objective Bayesian optimization-based co-design of neural networks and hardware, which results in efficient neural networks in the edge computing platform that achieve real-time processing ability [56].

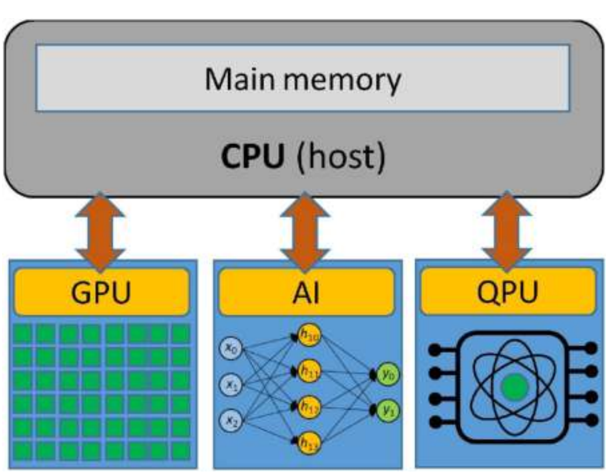

Fig. 4. The accelerator model of computing, such as GPUs, AI accelerators, or QPUs. Reprinted from [50], Copyright (2024), with permission from Publisher.

2.3. Tensor processing units (TPUs)

These specialized hardware accelerators, called TPUs, are engineered by Google to improve the speed and efficiency of AI and ML workloads by optimizing tensor operations at the core of deep learning algorithms. The TPUs are specialized or application-specific processors that are an alternative to general-purpose processors but are designed specifically for DNNs workloads, which are often multiply-accumulate (MAC) intensive, most often in the form of matrix-matrix and matrix-vector multiplications [57]. By employing systolic arrays for their architecture, TPUs were designed to maximize data reuse and minimize data transfer, leading to large performance improvements compared to conventional GPUs [57]. By delivering high throughput and low latency, TPUs have enabled many more improvements to machine learning tasks, both in cloud and edge computing applications, for example, in natural language processing (NLP) and computer vision [58]. The emergence of flexible TPU architectures, such as the Flex-TPU, further improves this performance by enabling dynamic reconfiguration of dataflow at runtime and achieving up to 2.75 times the performance of conventional TPUs with low overhead [57]. TPUs serve as an illustration of an increasing effort in AI hardware acceleration, as they are specifically designed to fulfil the accelerated computational needs of AI applications, thus outperforming general-purpose GPUs in certain scenarios [59]. Such hardware accelerators, TPUs being one prominent example, need to evolve to support emergent complex algorithms and larger data volumes embedded in current AI systems [60].

2.4. Field-programmable gate arrays (FPGAs)

Among these options, the FPGAs are playing an increasingly important role in developing accelerated hardware for AI workloads, given their reconfigurability and their use in optimizing hardware specifically for a given type of workload—essential for real-time AI applications such as autonomous vehicles or edge computing. FPGAs are a flexible approach to AI acceleration, as they enable hardware programming after manufacturing and are therefore critical for deploying complex models, e.g. vision transformers (ViTs) on edge devices. While these models have proven robust, they require significant computation resources, which FPGAs can help deliver for optimized inference accelerators on the edge, enabling real-time processing [61]. FPGAs enable real-time defect detection and decision-making in advanced driver-assistance systems (ADAS) for autonomous driving, and they employ various platforms, like AMD Xilinx, to implement high accuracy and efficient models, such as YOLOv3 [62]. While FPGAs can offer great performance, they have yet to penetrate the AI domain significantly due to their relatively complex setup that requires a deep knowledge of hardware design, optimization, and implementation; ecosystems were built to make FPGA simpler to use, providing off-the-shelf accelerators and APIs to abstract all that awful design away and make them adopted by many more people [63]. Moreover, applications that require energy efficiency would benefit from efficient hardware implementations on FPGAs, especially neural networks, which are optimized to reduce the area and power consumption while providing sufficient performance [64]. This progress highlights FPGAs' game-changing potential in AI, providing high-performance, low-latency solutions for an expanse of applications [35].

2.5. Energy-efficient AI electronics

The complexity of AI models is developing quickly, and there is a need for power-efficient electronics to help achieve high-performance computing without high power consumption. Advances in low-power system-on-chip (SoC) designs and energy-efficient processors are crucial to tackling this challenge, especially for AI applications on edge computing and mobile devices. An area that offers a compelling approach is neuromorphic computation—information processing inspired by the energy-efficient processing capabilities of the human brain. Such work presented an energy-efficient neural network using spintronic domain wall device-based neurons, with significant energy savings while maintaining high accuracy, paving the way for more efficient neuromorphic systems [65]. The high dimensionality of AI allows the generation of synthetic data from the underlying data distribution, which, in turn, is used for further training. Silicon has dominated the microelectronic world for years.

Nevertheless, silicon photonics platforms are already being developed to reduce the energy consumption of AI hardware, which serves as a fundamental building block of current and next-generation AI [66]. Novel energy-saving methodologies in the 5G spectrum utilizing AI (such as knowledge distillation, which reduces the model's size while preserving performance) are already being used to enhance AI for 5G, primarily per the DeepRX use case [67]. Moreover, different quantization schemes based on GPT-Generated Model Language (GGML) and GPT-Generated Unified Format (GGUF) reduced energy consumption in AI model inference and were highlighted as salient approaches towards energy efficiency [68]. Lastly, research and exploration of new computing in-memory architectures have also been achieved using negative capacitance field effect transistors (NCFETs), which have the potential to reduce energy consumption in AI edge devices significantly, showcasing the ability of next-generation devices to empower energy-efficient AI operation [69]. These improvements enable us to run AI models on edge devices and maintain long battery life and optimal power usage. An example from 2021, Fig. 5, shows the water withdrawal and energy consumption of 27 semiconductor manufacturing companies [70]. The correlation between water withdrawal (x-axis) and energy (y-axis) found strongly on the graph ($R^2 = 0.93$) indicates existing of high regional and operational deviations between Asian, American and European semiconductor corporations. To measure this, Asian firms such as Samsung lead in the energy consumption category. It is an example of a large-scale operation that requires enormous resources. It aligns with the findings that the semiconductor industry is one of the largest water consumers, with a total water withdrawal of $7.89 \times 108\ m^3$ and energy consumption of 1.49×1011 kWh in 2021 [70]. Semiconductor processes like layering and diffusion require considerable energy, which is evident considering that 83.7 % of the energy consumed by the industry comes from electricity [71]; additionally, the geographical pattern of water consumption reveals its implications on countries such as China and Southeast Asia, where semiconductor production is booming and may worsen local water scarcity [72]. The Water-Food-Energy nexus approach indicates the need for sustainable practices and policies that govern the industry's environmental footprint [73].

The challenges of incorporating AI into RE systems are discussed in Fig. 5. The need for more extensive and better-quality data to improve the predictive modeling of event occurrences and to be able to optimize the systems is one of the main challenges in this area [74,75]. A representation of the most common problems and challenges in the predictive maintenance of RE systems is illustrated in (Fig. 6) [76]. Another important aspect of training is parameter tuning and fault modeling, where AI systems are expected to adjust to the dynamism and uncertainty of RE sources such as wind and solar panels [75,77]. Moreover, energy storage and integration with the power grid present unique challenges; thus, AI is employed to help with optimizing energy flows and maintaining grid stability [75,77]. AI model explainability plays an important role in performance monitoring and decision-making, yet it remains a challenging issue because of the black-box nature of many AI algorithms [74,77]. Security issues such as data breaches are the most critical ones. Hence, integrating AI with cybersecurity is vital to safeguard energy systems from cyber-attacks [78]. Optimizing AI-driven renewable technologies is another challenge that has to do with balancing many constraints, including cost, efficiency, and environmental impact [79]. However, breakthroughs in ML, reinforcement learning, and new technologies such as blockchain and digital twins provide exciting solutions to improve the efficiency and sustainability of RE systems [77,78]. Tackling these issues is critical for realizing the

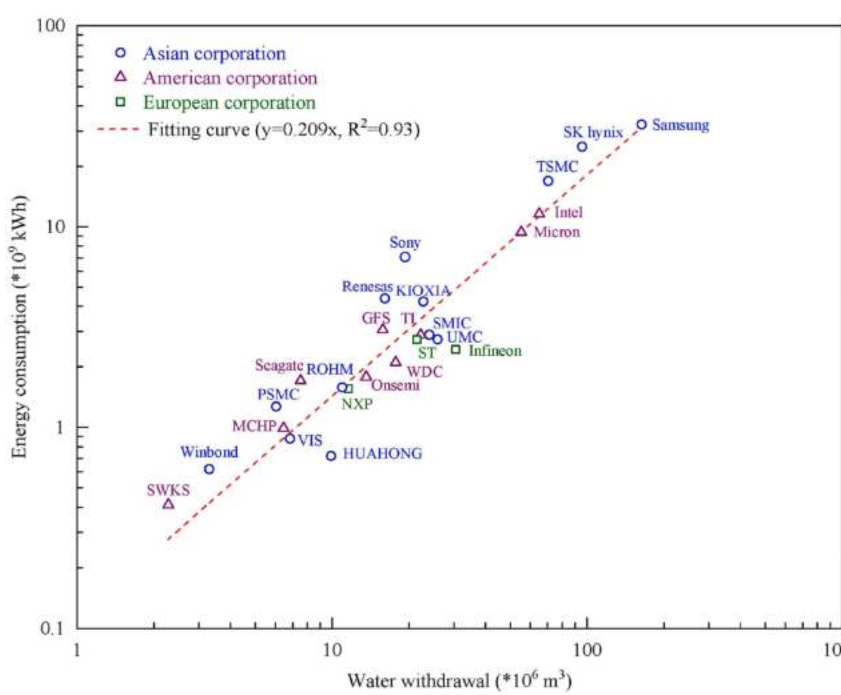

Fig. 5. The energy consumption and water withdrawal of the semiconductor corporations in 2021. Reprinted from [70], Copyright (2023), with permission from Publisher.

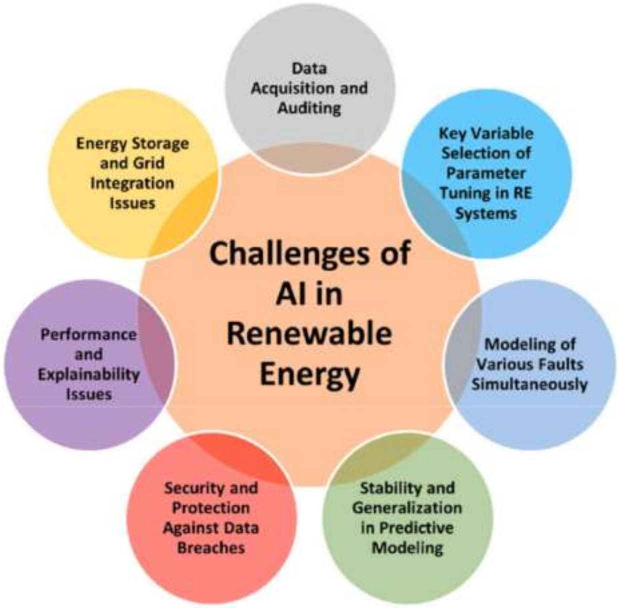

Fig. 6. The challenges and open issues of AI approaches in RE systems. Reprinted from [76], Copyright (2024), with permission from Publisher.

Sustainable Development Goals (SDGs) and securing an energy future that is safe, reliable, and sustainable [78]. With the world increasingly grappling with environmental issues [80] like climate change [81,82], resource depletion [83], and biodiversity loss [84], adopting new technologies to create sustainable approaches to overcoming ravaging obstacles is essential—environmental aspirations of AI powered by electronic competitiveness. AI has emerged as a solution to many complex environmental problems like climate change, waste management, and natural resource conservation, as it can automate the analysis of substantial amounts of data [85]. AI algorithms, for instance, can monitor and predict environmental variables when integrated with advanced sensors and IoT devices, providing real-time insights for better decision-making.

2.6. Quantum computing

Quantum computing is still nascent but has significant potential to drastically improve AI systems capability beyond classical semiconductor-based systems found in traditional computer systems. Electronic development has led to speedups in computer technology and five generations of computers, as shown in Fig. 7. The narrative follows that computer generations represent milestones in computational architecture along with computational speed, size, and intelligence dimensions. The fifth generation, which is focused on AI, will be the next step in the development of computing; efforts to produce true intelligent machines through software breakthroughs seem inevitable [86]. This

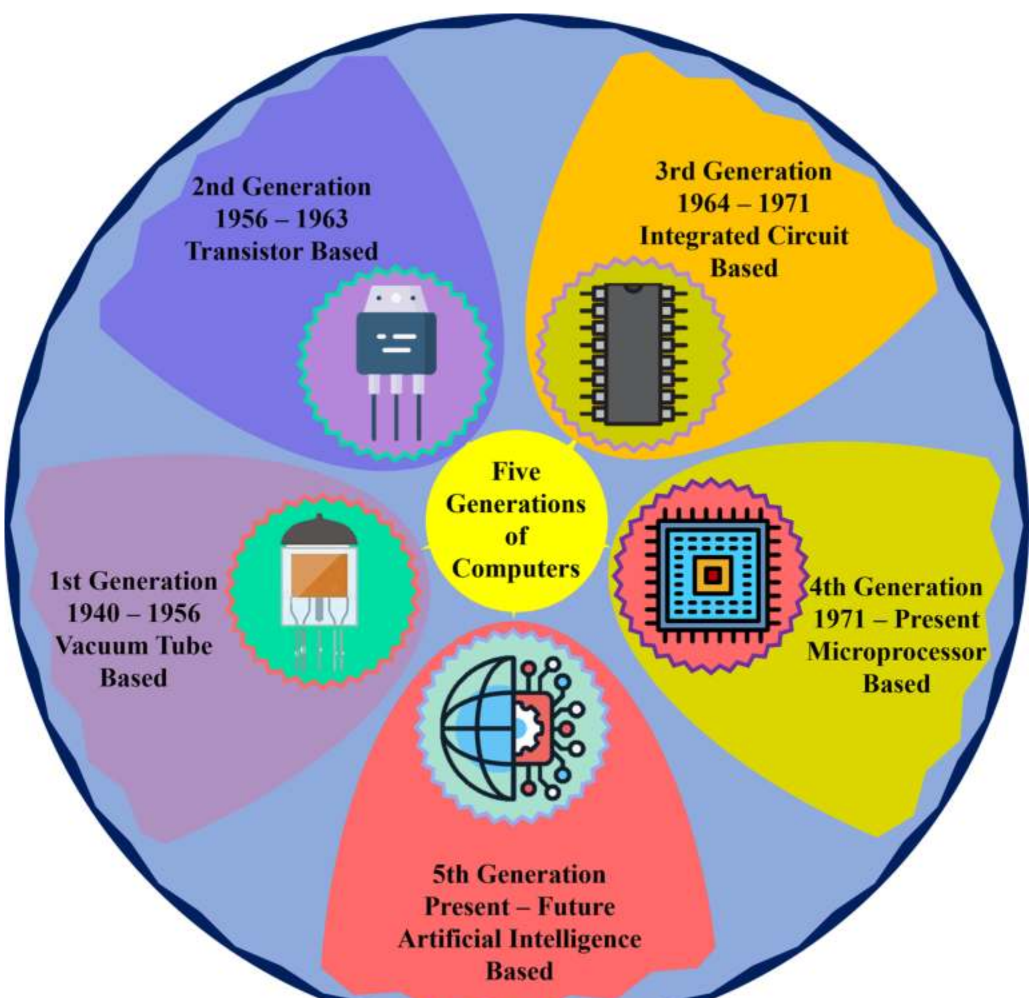

Fig. 7. Five generations of computers.

shift from vacuum tubes to AI-enabled systems highlights the cross-domain roots and constant advancement of computing technology, as from simple computing machines, computers have transformed into intricate intelligent frameworks [87]. Suppose quantum computers are known to achieve exponential acceleration over ultra-large-scale parallel computing tasks [88]. In that case, they use qubits that leverage quantum superposition and entanglement, thus performing a given calculation at speed inaccessible to classical computers; such capability is very well coupled with AI applications, as quantum algorithms like quantum support vector machines and quantum neural networks have the potential to improve machine learning by efficiently handling large data sets and solving significant optimization problems [89]. Furthermore, quantum computing can greatly enhance computational performance in climate modeling, allowing more precise forecasts and sustainable development plans [90]. Moreover, quantum computing has broader implications for cryptography and material science, as it would redefine the limits of problem-solving and data processing, allowing complex simulations and optimizations to be performed quickly and frequently [91]. However, the practical realization of quantum computing is still evolving, and much work is being done to address issues related to qubit stability and error correction [92]. There is a great deal of activity in this space as quantum hardware and algorithms mature rapidly, unlocking new AI applications, such as significant progress in drug discovery, climate resilience, cryptography, and many more, ushering in a new era of discovery and innovation.

2.7. Neuromorphic computing

The hardware systems of neuromorphic computing are an improvement over previous attempts to replicate the human brain's structure and function with a nanocomputer and soft computers, providing potential applications for tasks as diverse as pattern recognition and sensory processing in areas like robotics and autonomous systems. These systems adopt SNNs that allow for parallel and asynchronous processing methods similar to biological neural activity [93]; this leads to improvements in computational performance and energy efficiency of up to 99 %. For instance, the design and fabrication of floating gate-modulated photoelectric synaptic transistors have been studied to integrate biological synapse-like functionalities on silicon substrates, where designed synaptic transistors can even achieve high accuracy of pattern classification, as much as up to 94.65 % for Modified National Institute of Standards and Technology's (MNIST) handwritten digits [94]. Moreover, integrate-and-fire neurons have been adopted in reservoir computing systems such as Intel's recently announced Loihi architecture, one of several low-power, task-specific neuromorphic designs capable of efficiently processing chaotic dynamics and carrying out time series prediction tasks [95]. Moreover, the reconfigurable neuromorphic computing section based on various 2D material heterostructures highlights the versatility and energy efficiency of these systems, capable of not only emulating the critical parts of neurons but also performing complex tasks of neural network-based information processing [96]. This latest spree of innovations in neuromorphic computing when clean win as they not only trespass the age-old challenges of Von Neumann architectures but also shape an impressive renaissance prospect in efficiency to usher in brain-like processing abilities for AI systems featuring real-time decision-making and learning.

3. Building blocks of AI algorithms

So, the AI algorithm development is so different and cannot see a parallel. However, electronics development is very much correlated with AI development because the required hardware to run and scale complex AI is electronics. Introducing sophisticated ML and deep learning models has resulted in a growing need for high-performance and energy-efficient electronics. Now, while the semiconductor industry does not refer to this new SoC as AI system-on-chip (AISoC), the offered features are part of the AISoC world, and only some of the features above fit into the eight points exactly, but the solutions offered by various semiconductor companies are undoubtedly a step in the right direction, as shown in (Fig. 8) [97]. The AISoC is a powerful hardware-software integrated solution to augment AI-enabled applications with improved performance and scalability. This system focuses on low-cost manufacturing and performance-per-watt efficiency, supported by hyper-parallel and pipelined architectures that reduce external memory access and allow data to be exchanged through high-speed interconnects [98]. The architecture on-chip is built on the principles of hardware-software co-optimization across architecture, circuit and process technology, and it is scalable with advanced technology nodes and high-speed memory, providing seamless programmability and reducing bottlenecks, resulting in overall excellent improvements in AI deep learn performance [99]. AI chips and AISoC can have peculiar design features such as data parallelism and storage optimizations, as demanded by the rapid increase in requirements by deep learning models [100]. For example, the application of silicon photonics platforms has been recognized as a critical technology for next-generation AI hardware, providing a considerable boost in energy efficiency [66]. Despite challenges with cost and market monopoly [53], specialized chips like GPUs and TPUs are critical to improved performance in AI systems, especially for deep learning workloads. Moreover, the energy efficiency of AI algorithms is a crucial aspect of sustainable computing, where research has focused on reducing the energy demands of an algorithm with careful and upfront design of its components or with the hardware it runs on [101]. Neural networks are most well known for their outstanding performance in many applications, yet hardware accelerators are indispensable for their energy-efficient performance, thus making AI ubiquitous [35]. Moreover, applications involving artificial intelligence in designing high-frequency magnetic components for power electronics systems further highlight how AI can increase the efficiency and innovation of electronic components design, emphasizing the interdependence of AI with electronics [102]. These recent developments highlight how critical electronics allow increasingly complex and data-intensive artificial intelligence and ML systems to achieve breakthroughs in computer vision, NLP, and autonomous systems. However, the AISoC is a game-changer for AI hardware, as it allows for more intensive computing closer to the cores and sets the stage for other advances in AI chip development.

3.1. Making high-performance computation accessible

Deep learning relies on the ability to perform complex mathematical computations, as well as on hardware that can manage these heavy tasks. Traditional CPUs are general-purpose processors that are not optimized for the parallel processing needs of AI workloads, prompting the use of specialized hardware that runs the risk of being developed as slowed digital torture devices. This is especially true for GPUs that have transformed AI development to their capability to execute thousands of instructed tasks in parallel and, therefore, essential for the concurrent training of deep learning models since they are optimized for parallel processing of matrix operations [60]. Such specialized chips are driving the performance of AI systems [53]. Moreover, designing efficient architectures is the foundation of DNN accelerators, including VLSI-based hardware accelerators [59], and optimizing power and space is an integral part of developing edge-AI applications [103]. To reduce the amount of data transferred and hence the energy expended, novel architectures such as CIM architectures that tightly couple processing and memory elements are promising solutions for improving the performance of neural networks [104]. Such technological progression of hardware programming accelerates significantly and helps unleash AI's potential and advances in a way that cuts across critical domains [35].

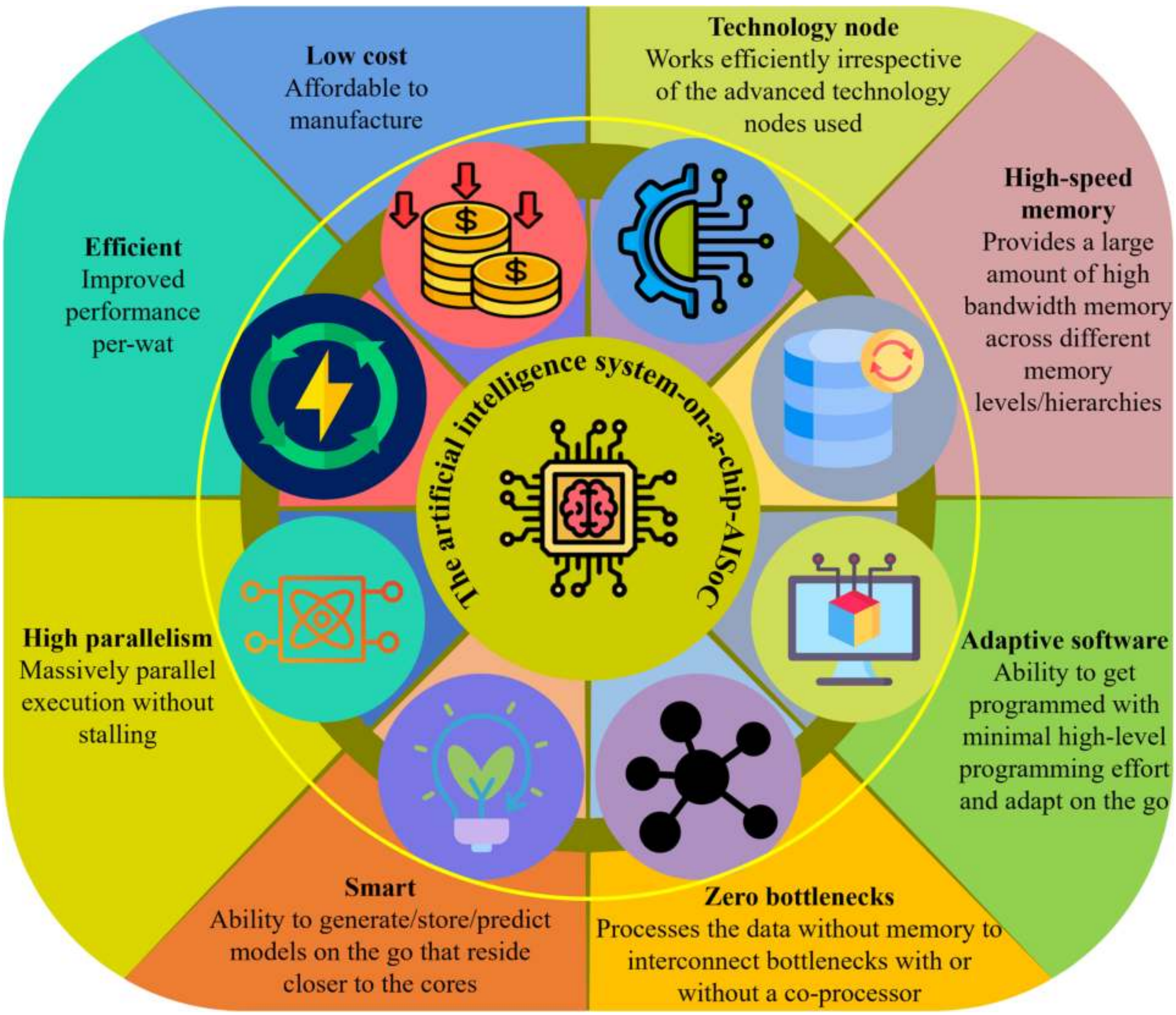

Fig. 8. The eight-point features solution for AISoC. Source [97].

3.2. Model training and inference acceleration

This DNN, widely used in NLP and image classification, benefits from advanced hardware accelerators, including GPUs, ASICs, and FPGAs, to significantly improve training and inference performance. These accelerators are vital for training large models on scale and accessibility with reduced training times. As an example, GPUs and FPGAs are emphasized on their capability of fulfilling the computation-intensive workloads of deep learning for real-time inference in applications such as self-driving [105]. Deep learning methods in EDA tools are another evidence of the need for AI to speed up chip design, recalibrating performance, and power consumption to facilitate running AI more efficiently [106]. Additionally, advancements in high-performance computing (HPC) strategies exemplified through the parallelized stochastic gradient descent algorithm highlight the opportunities for improving training times with faster convergence times and increased computational efficiency, an essential aspect for deploying AI models within resource-constrained ecosystems [107]. These developments in hardware and optimizations aid in faster training and deployment of AI models but also help make AI more approachable and viable for a range of industries [32]. From AI algorithms to hardware accelerators, their synergy is vital to changing the ways to apply AI since this deals with whether models will be capable of producing fast and correct outputs under real-world circumstances [35]. Fig. 9 displays developed powers AI strategies, each of which has ranged long-term systems for the advancement and convenience of AI innovations [108]. From 2017 to 2018, several countries produced AI strategies, revealing their priorities around AI; for example, the Pan-Canadian AI strategy of Canada [109] focuses on funding innovation and aims to position Canada as a research and development center for AI. Through the AI Strategy, Japan aims to integrate AI technologies into real industries to promote economic growth and solve social problems [109]. The EU AI Framework emphasizes regulation and ethical considerations, reflecting the European Union's desire to curb the influence of AI [109]. On the other hand, the United States advocates for a more hands-off approach towards AI through the White House AI Summit and similar initiatives, calling for leadership and innovation from the private sector [109]. Representatives from more than 60 countries are already developing national-level AI strategies, which are part of a growing global momentum to balance the potential of the technology with the challenges around issues such as data privacy, ethical use and international co-operation [110]. The Organisation for Economic Co-operation and Development (OECD) has been central in promoting international agreements that set out principles for AI, helping governments find a balance between enabling innovation and implementing regulation.

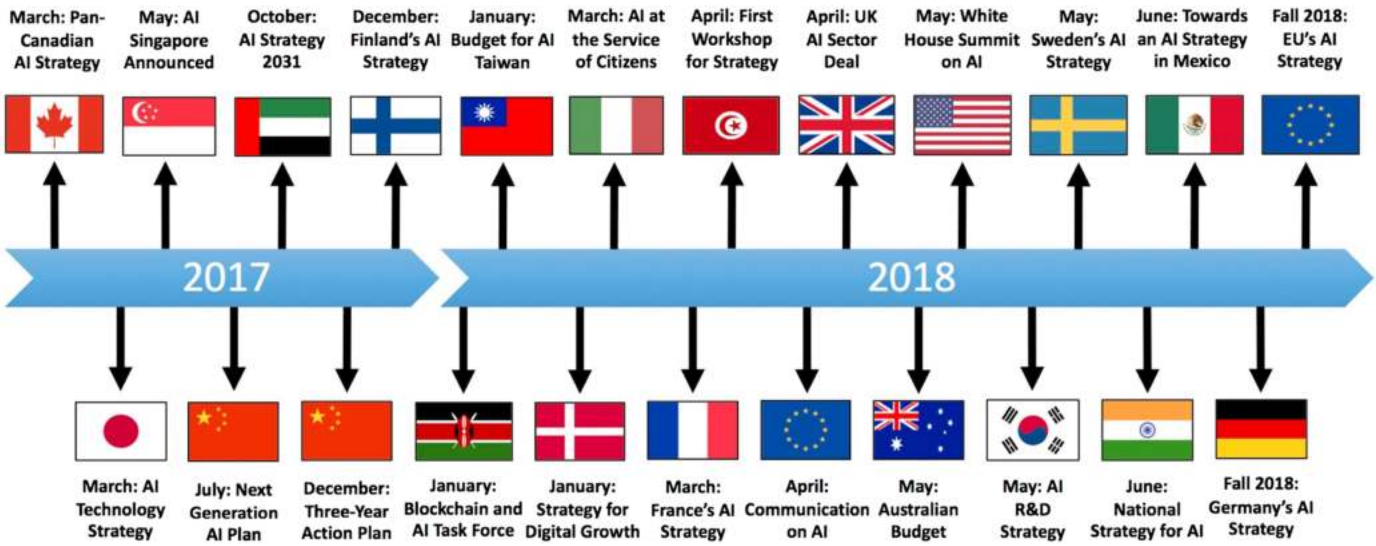

Fig. 9. Overview of AI strategies: The developed nations are choosing and working on new state-of-the-art AI technologies. Reprinted from [108], Copyright (2021), with permission from Publisher.

3.3. Allowing distributed and parallel computing

The increasing complexity of AI algorithms and the size of datasets require distributed computing and parallel processing, methods that are common in non-AI workloads, to tackle big AI workloads. Many modern AI models, especially in deep learning, opt to use distributed high-performance computing techniques built around data, model, and pipeline parallelism and hybrid implementations for efficient training of large AI models. The scalability challenges in distributed systems necessitate specialized algorithms like distributed optimization algorithms and communication-efficient algorithms like Ring All Reduce [111]. Data centers provide scalable infrastructure thanks to extensive hardware resources such as processors, GPUs and TPUs and enable the convergence of model training and deployment by making infrastructure costs low and global scalability achievable for AI [112]. Edge-based computing also uses AI models that run on local devices for real-time processing without requiring centralized cloud services. Distributed edge training based on decentralized trusted edge devices allows for the taking advantage of idle resources for sustainable and efficient training of large AI models at the edge, representing an attractive solution to privacy and energy issues of training in a centralized fashion [113]. Especially for the next-phase 6G networks, the intelligent node selection and data allocation strategies make it possible to accelerate distributed training by optimizing the allocation of computational tasks across all the network nodes [114]. Such advances in distributed computing and electronic components are instrumental in handling parallel and distributed workloads when executed in large-scale AI applications across appraising environments [115].

3.4. Innovations in memory and storage

In deep learning, the execution of AI algorithms becomes highly memory-consuming due to the extensive storage requirements for the training data, model parameters, and intermediate computational values; accordingly, improvements in memory technologies have considerably aided this process. High-bandwidth memory (HBM) has arrived as a vital solution to meet the increasing computation requirements of modern AI models, including such models as generative AI models like GPT, where speed and capacity are a critical concern, though they face hurdles [116]. As a result of their capability to operate by performing computations in the memory arrays, features such as CIM reductions in both data movement and energy consumption, non-volatile memory (NVM) technologies such as phase-change memory (PCM), and quantum-dot transistors have been investigated for CIM applications. These devices aggregate compute blocks and are especially advantageous for DNN accelerators, allowing for high-throughput multiply-accumulate computations, leading to energy-efficient computing [104,117]. Furthermore, 3D DRAMs deliver high memory bandwidth, which is vital given that DNNs are compute-intensive; however, they also need to perform intelligent data mapping to minimize thermal degradation while improving overall performance [118]. At the edge, memory optimization techniques like memory integration controller (MIC) have been proposed to cope with memory limitations that promote instrumenting various memory optimization techniques together to conduct efficient DNN training and inference [119]. These advancements in memory technology work together to support higher data transfer rates and a more efficient use of memory, enabling AI systems to process larger datasets and more complex models effectively.

3.5. Allows edge AI and real-time processing

Advances in specialized, low-power electronics are playing a significant role in the shift towards edge AI: the move to deploy AI algorithms directly on devices rather than in centralized data centers. Electronics are crucial for edge devices like smartphones, wearables, and autonomous vehicles to locally run complicated AI models in real-time, facilitating tasks such as object identification and speech recognition while minimizing latency and alleviating privacy issues by processing data on-device [120]. Innovations in edge processors, including low-power AI chips and AI accelerators [121], are essential in this regard, assisting in executing efficient inference without relying on cloud connectivity. These include dataflow, neuromorphic processing in-memory (PIM), and others, each providing benefits in terms of energy efficiency and specific applications [122]. The merger of AI, ML, and IoT into automotive paradigms can highlight the potential of edge computing to realize its superiority, especially in terms of a higher-level user experience and enhanced safety in constrained environments [123]. The fast-paced evolution of edge AI will make overcoming challenges like scale and security vulnerabilities and systematic taxonomy and collaborative learning systems [124] both relevant parameters showcasing its transformative impact across industries like healthcare, robotics, smart cities, etc. Edge AI is an evolving technology that is expected to transform the way technology services are rendered in society, giving rise to pervasive AI services [120].

4. New electronics for AI applications

In fields like healthcare, autonomous systems, and industrial automation, the need for such specialized electronics to enable performance, efficiency, and scalability has led to rapid developments in AI [1]. New electronics technologies, such as hardware accelerators, will be critical to addressing the computational burden of complex AI algorithms. In addition, ASICs, TPUs, or GPUs have substantially improved machine learning workloads, allowing more complex AI functions to work as a system [60]. AI systems are transforming diagnostics, treatment planning, and patient care [125]. AI integrates big data and ML, improving workflows and patient outcomes through healthcare analytics [126]. Another area leveraging AI technologies is EDA, as the advent of deep learning-based methods [106] provides features to the chip power prediction and optimization aspects that improve design performance and layout efficiency in the semiconductor industry. These advancements highlight the importance of new electronics supporting AI innovations in all fields, needing continuous exploration and cooperation between the AI field scientists and designers of AI-supporting hardware to overcome problems and fully employ AI capabilities [2].

4.1. Neuromorphic computing

By emulating the structure of the human brain, neuromorphic computing is a massive breakthrough in AI research that makes up for the shortcomings of modern computing by improving memory capacity and combating Moore's law memory wall. In contrast, specialized circuits model the behavior of neurons and synapses to achieve computational capabilities and low power consumption, which are of utmost importance in edge AI applications such as robotics and autonomous driving [93]. Examples of neuromorphic chips are Intel's Loihi and IBM's TrueNorth, which use SNNs, allowing for parallel and asynchronous data processing similar to that observed in biological neural activity that provides significant advantages in power consumption and computational efficiency compared to classical processors [127]. These chips can be realized using multiple neuron models, such as HH and Izhikevich models, and can utilize analogue, digital, or hybrid systems with different memory topologies [93]. Moreover, the discussion of two-dimensional materials such as graphene significantly improves the device performance with the unique electronic performance of two-dimensional materials, which is conducive to rapid synaptic and neuronal emulation in AI and sensor networks [128]. While neuromorphic computing shows excellent promise, challenges, including memory integration and scalability complexities, persist, requiring further investigation and possible integration with quantum computing principles to leverage its capability in real-world applications.

4.2. Quantum computing

As a new and upcoming electronics paradigm, it has immense potential, especially in the AI era, as the computation power can increase by several orders of magnitude. Traditional computers use binary bits, but quantum computers use qubits, which can represent multiple states simultaneously, to quantum phenomena like superposition and entanglement. This allows quantum computers to compute some problems much faster than conventional machines, leading to exponential speedup for specific problems [129]. This could substantially increase AI applications, improving the capacity to handle vast datasets, run intricate simulations, or optimize machine learning algorithms within quantum computing frameworks. Quantum support vector machines and quantum neural networks, for example, use these principles to study large volumes of data more quickly, accelerating tasks such as optimization, pattern recognition, and data classification [89]. Quantum accelerators and quantum algorithms would make it possible for AI systems to address more complex tasks, including but not limited to drug discovery, materials science, and cryptography [130]. Although it is still in the infancy stage, quantum computing has drawn considerable attention for its potential to address specific AI challenges, including accelerating the training of AI and enhancing pattern recognition [131]. Furthermore, in the IoT field, quantum computing can revolutionize data processing by significantly decreasing the time taken for data analysis, facilitating real-time processing potential even with large-scale datasets [132]. The possibility of such transformative potential is an impetus for ongoing research and development in quantum computing to harness its full power for AI and more.

4.3. Edge AI processors

AI computations can occur on edge devices, especially with Edge AI processors like Google Edge TPU, NVIDIA Jetson, etc. These would have significant benefits, such as low latency, real-time processing, and energy efficiency. For example, these allow real-time processing of sensor input (such as those from cameras and LIDAR) used on machines for tasks such as autonomous vehicles, which are highly latency-sensitive, as software for autonomous vehicles must frequently interface with hardware [120]. Edge AI is a further advance in terms of movement, driven by the growing need to process data closer to where it is generated, reducing latency and the demand for bandwidth, such as the work done for the Edge AI Based Object Detection System using TensorFlow Lite, which has been able to accomplish real-time object detection in lightweight devices [121]. The design of edge processors, including dataflow processors, neuromorphic architectures, and PIM processors, heavily impacts their performance, with PIM showing good energy efficiency [122]. Moreover, when utilized in Parsomonias for multiprocessor system on chip (MPSoC) architecture, FPGA-based solutions for edge computing such as this can increase computational efficiency and system-level performance for deployment in mobile edge computing environments [133]. The development of edge AI processors is leading to significant changes in the industry, enabling intelligent use cases across platforms to be light, fast, and ubiquitous. However, the Industrial Revolution 4.0 differs from the Internet of Energy (IoE), the IoT, and the Industrial Internet of Things (IIoT), as shown in Fig. 10, so now in the 21st century, revolution is linked with the cyber-physical system (CPS) [134]. Each industrial revolution has brought forward technological innovations that fundamentally changed manufacturing and conducting business. Industry 3.0 emerged in the 1970s as programmable logic controllers (PLCs) that supported automation, electronics, telecommunications, and computing in manufacturing [135]. Nowadays, Industry 4.0 is propelled by cyber-physical systems (CPS), which integrate IoT, AI, and advanced connectivity to develop smart manufacturing systems [136,137]. The Industrial Revolution has enabled digitalization and production automation, making manufacturing processes flexible, efficient and eco-efficient [138].

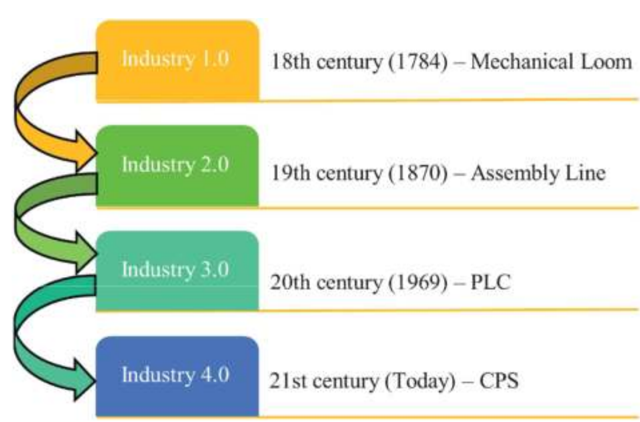

Fig. 10. History of Industry 4.0. Reprinted from [135], Copyright (2020), with permission from Publisher.

Modern Industrial 4.0 includes technologies like big data analytics, cloud computing, robotics, and 3D printing, which has improved the time needed to process data and make real-time decisions [139]. This dramatic potential for economic, political, and social value creation leads China, the USA, and other countries to develop a national strategy around the emergence of AI and automation [139].

4.4. Photonic computing

Photonics, which uses light to transmit and process information, has the potential to significantly improve the speed, bandwidth, and energy efficiency of AI workloads. This technology could speed up increasingly compute- and memory-intensive workloads like DNNs. This enables novel engineering of optical devices and circuits to flexibly accommodate multiple DNN tasks, boosting performance and energy efficiency on diverse platforms, from embedded to IoT systems [140]. Other photonic technologies—including microring resonators—are being investigated to implement analogue neuromorphic computing as a workaround to the Von Neumann bottleneck, enabling AI processing to speed up and be done more efficiently [141]. Recent developments in high-speed, low-power consumption optics (primarily via silicon photonics) have led to pluggable modules and active optical cables tailored for AI/ML use cases, emphasizing optimizing their performance and power consumption [142]. As these operation modes converge with deep learning models and large datasets, so too do the development of large-scale integrated photonics platforms that execute AI algorithms in increasingly energy-efficient ways [66]. On the other hand, photonic neural networks, including programmable photonic extreme learning machines, exhibit low latency and energy efficiency despite limitations in training algorithms (like backpropagation). Other approaches have included

Fig. 11. AI in healthcare.

so-called extreme learning machines, which present the opportunity to simplify the training, proving that photonic processors could support competitive machine learning models [143]. These developments imply that photonic computing may have considerable implications for AI cases demanding high-speed, high-volume data processing like real-time video analytics and large-scale data center executions.

4.5. Flexible and wearable electronics

The convergence of artificial intelligence with flexible electronics and wearables is set to transform fields as wide-ranging as healthcare, sports science, and human-computer interaction. AI is revolutionizing the healthcare industry, from predictive analysis to robot-assisted surgery and drug discovery. AI in such systems enhances clinical decision-making and medical imaging diagnostics, leading to greater efficiency and precision in patient care. AI algorithms are embedded in wearables, allowing for real-time data interpretation and analysis of psychological and physiological states and helping to personalize healthcare diagnostics. For example, using data from wearable sensors, predictive systems powered by AI efficiently predict the mental state with high accuracy by processing time-oriented and sequential data through convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [144]. AI applications in this field have allowed the creation of advanced human-machine interfaces through improved neural signal processing (e.g., EEG, ECG) and biomedical applications of intelligent interfaces [145]. So, Fig. 11 illustrates the fundamental role of AI in healthcare. An application of AI algorithms in various fields could be processing significant amounts of medical data by AI behaviors that allow healthcare professionals to make accurate diagnostic decisions and prescribe personalized treatment [146,147]. In surgery, robotic solutions optimized by AI allow greater precision with less risk than conventional manual surgery, producing better patient outcomes at lower cost [148]. AI applications in telehealth, including virtual assistants and remote monitoring, also greatly increase patient care accessibility and engagement, especially in rural or underserved areas [148,149]. AI is also instrumental in speeding up drug development and clinical trials, significantly lowering the time and expenses of introducing new drugs to the market [147]. A practical case of this is the development of wearable devices for cardiovascular monitoring, where models based on long short-term memory (LSTM) architecture predict and detect anomalies in the heart rate and ECG data stream, thus permitting proactive health management [150]. Nevertheless, implementing AI in wearables also has risks, especially for data privacy and automation in decision-making, which requires thorough risk assessment [151]. The wearable AI landscape is also being discussed in the context of the Human-Inspired Distributed Network and the `Body as a Wire' technology, which would open up the possibility of secure inter-device, low-power connectivity, the function of the user devices, and sequential data storage [152]. So, the confluence of AI and flexible electronics within wearables stands to drive significant progress in personalized and connected medical solutions.

4.6. Autonomous systems require high-performance AI chips

High-performance AI chips designed for autonomous systems demand specialized high-performance electronics to process massive amounts of sensory data, a core trend in AI-driven systems. Reality is more ambitious for NVIDIA and Tesla, one of the leading companies manufacturing AI chips that provide real-time processing for object detection and path planning, which are used for flying and driving vehicles and robots. They are tailored to the computational requirements of autonomous systems and optimized for low-power operation [100]. Embedded AI vision systems, which bring an AI element into a vision pipeline, are transitioning from cloud-based processing to near-sensor and in-sensor processing architectures. Such transformation overcomes issues associated with obstructions to data, such as access to high data or power consumption, by reducing the cost of transfer and latency and enabling real-time operations under a limitation such as efficiency [153]. AI integration with sensor technology boosts the accuracy and adaptability of sensing technologies, which have had advantages in areas such as robotics and biomedical engineering [154]. In the case of autonomous vehicles, AI-based image processing is of utmost importance, especially in algorithms like CNNs and RNNs, to overcome challenges such as semantic image segmentation and 3D object detection [155]. Moreover, this synergy of multi-sensor hardware with artificial intelligence methods maintains obstacle detection, ensuring more effective hazard detection and increasing safety reliability for autonomous vehicles [156]. The advancement of AI chips will further facilitate innovation in other industries, such as transportation, logistics, healthcare, and defense, ultimately creating better autonomous systems [100]. Fig. 12 represents the nations participating in the semiconductor production [157,158]. According to previous findings, the semiconductor market is increasingly application-driven. The dominant application-driven demand is from AI and the IoT, which require advanced semiconductor technologies for data acquisition (e.g., sensors), specialized AI hardware, and economical implementations like NB-IoT [159]. Over the past decade, the semiconductor ecosystem has been significantly influenced by the proliferation of IoT devices and embedded systems, paving the way towards improved connectivity, low-power design and sensor integration capabilities to support smaller, more energy-efficient devices [160]. Recent disruptions to the semiconductor supply chain demonstrate the industry's global interdependencies and the potential economic impact of supply shortages across downstream industries, such as electronics and motor vehicles [161]. The semiconductor supply chain, essential for scientific development, economic growth, and national security, is a domain where the U.S. and its allies exert considerable leverage, begging for policy guidance to safeguard these supply chains and develop emerging technologies [162]. Moreover, the global value chain of the electronics industry is the archetype of growing complexity and fragmentation of production, with East Asia, especially China, at the epicenter of value generation that is increasingly driven by capital and high-skilled labour [163].

5. New frontiers in artificial intelligence for environmental conservation

In recent years, AI and machine learning applications have gained significant traction in environmental protection and conservation efforts, with researchers and organizations implementing innovative solutions to enhance environmental monitoring [164], conservation planning, and data analysis. Applications of AI technologies are proliferating for such purposes: to optimize resource use, monitor environmental conditions in real-time, predict potential risks, and inform decision-making processes across a wide range of environmental sectors. The use of AI technology helps to reduce pollution, ensure better management of the environment, and attain sustainable development goals [165]. AI can be used as an essential tool in major disciplines like natural calamity [166]. The critical advances in AI for protecting the environment address how AI promotes sustainability and improves our ability to respond to environmental disasters. The previous study indicates that global E-waste generation in 2030 will be around 74.7 million metric tons, and only 17.4 % of e-waste is formally collected and recycled globally, as shown in (Fig. 13) [167,168]. So, population growth, economic development, and technological innovation will increase the demand for natural resources [169,170]. However, this growing demand presents significant environmental challenges spanning climate change, biodiversity loss, and resource depletion [171]. According to previous research, waste generation is projected to grow from 2.01 billion tonnes in 2018 to 3.40 billion in 2050, where around 43 % of global solid wastes are improperly discarded, leading to practices such as incineration, illicit garbage dumping, open burning, and illegal landfilling [172]. Only a third of produced plastic is recycled; the

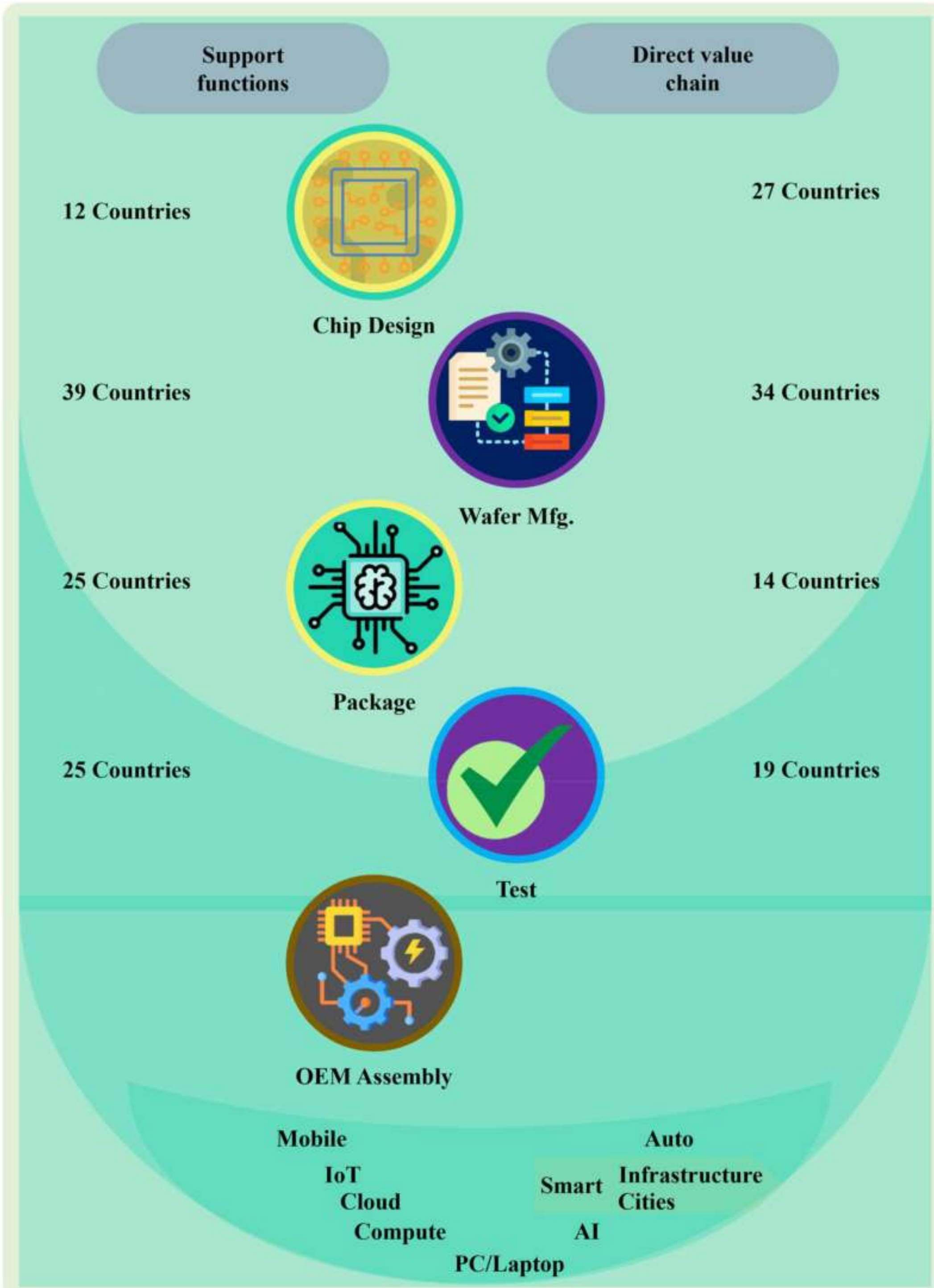

Fig. 12. Number of countries participating in semiconductor manufacturing. Source [157,158].

production and incineration of plastic releases roughly 400 million tons of CO_2 into the atmosphere each year [173]. In 2015, humans produced at least 6.9 billion tons of plastic waste, and 11 % of plastic waste enters aquatic ecosystems annually; despite the global efforts to reduce and manage plastic waste, around 53 million metric tons of plastic waste will still enter the water environment every year by 2030 [174]. Moreover, the shift toward a low-carbon arrangement will require responsible extraction and handling of the raw materials essential for green energy systems and infrastructure [170]. The displacement of extraction, with such taking place in Asia instead of North America and Europe, and the predicted spike in Africa make the sustainability landscape even more challenging, demonstrating that material consumption's environmental and socioeconomic sustainability can only be addressed via interdisciplinary collaboration [171]. Moreover, the transition to sustainable materials and circular economy provides ambitious policy settings that can help address these challenges [175].

5.1. *Sustainable electronics: positives from AI, negatives from E-waste*

AI is also becoming a powerful tool when combined with electronics

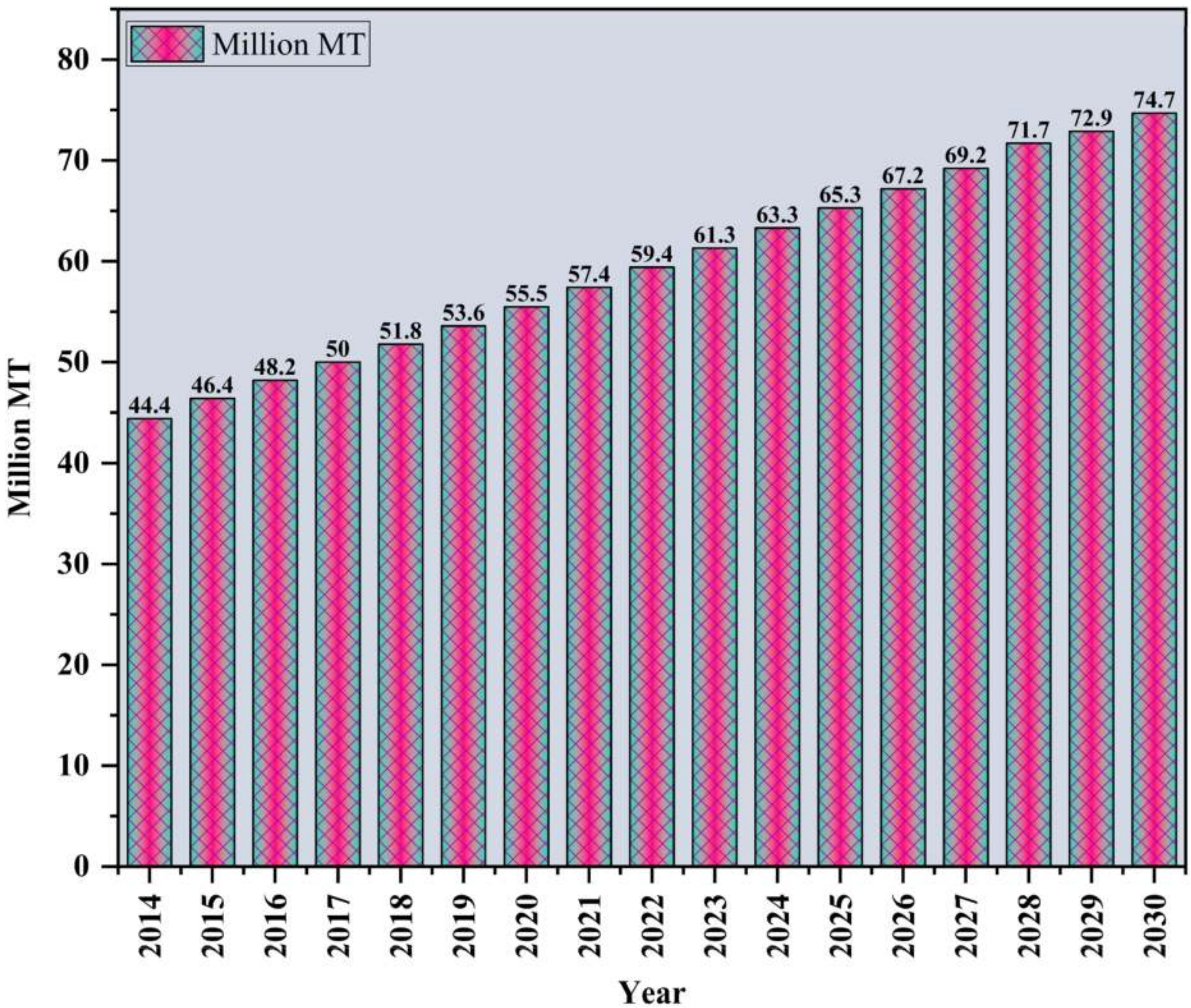

Fig. 13. Over the past several years, estimated global e-waste has been produced (in million metric tons). Source [168].

to help with environmental sustainability. AI ethical reflections and practices cannot bar numerous AI negative occurrences from human society to the environment [176]. There is always some level of inherent risk associated with every business venture [177]. Previous study shows that the rents for natural resources and mineral rent, with mineral depletion at 10 % significance, natural resource depletion at 1 %, and electricity generation from natural gas resources at 5 % material, so the sustainable development index correlates negatively with mineral depletion [178]. Natural resource utilization, particularly of mineral resources, has been an important factor in industrialization and urbanization, and their efficient management is a major contributor to economic and social advancement [179]. Integrating electronic systems with AI technologies presents a unique way to monitor, manage, and optimize environmental resources sustainably with minimal human impact on the planet. Here, we discuss how coupling these two disciplines enables environmental sustainability in various sectors. Environmental threats, especially from electronics development, are in the form of e-waste, as shown in Fig. 14. E-waste, which consists of degraded electronic systems, includes toxic components, like lead, cadmium, and polychlorinated biphenyls, that can lead to serious pollution and health problems if improperly handled [180,181]; however, lead is extremely toxic, especially to children [182]. Most liquid waste is classified as hazardous industrial waste that could severely harm the ecological environment and the health of the population if adequate control measures are not taken [183]. Especially in developing countries, severe infrastructure deficits or informal recycling processes increase pollution and health hazards [184]. However, safe recovery of resources and circular economy initiatives provide strategies for reducing these threats. ML applications and robotic automation are considered the future runners to accomplish a smart tomorrow toward minimizing environmental waste [185]. In addition, eco-design electronics and devices with minimal environmental impact make the e-waste less damaging, thus facilitating a change in this direction [186].

6. Challenges and limitations

Nevertheless, the breakthroughs in electronics have undoubtedly accelerated the advent of AI, but there are still bounds and restrictions. However, high energy consumption, hardware-software mismatches, cost and accessibility problems, scalability, and data privacy are significant hurdles. Such problems have become especially prominent regarding large-scale AI models and their use in practice. These issues are explored further in the following sections.

➢ AI systems, particularly those utilizing deep learning, can be power-hungry, resulting in high costs and environmental impacts. The eCAL (energy Cost of AIoT lifecycle) metric indicates that energy or carbon can play a crucial role in evaluating AIoT systems, and energy-efficient techniques are essential in AIoT systems regarding energy consumption and carbon emissions [187].

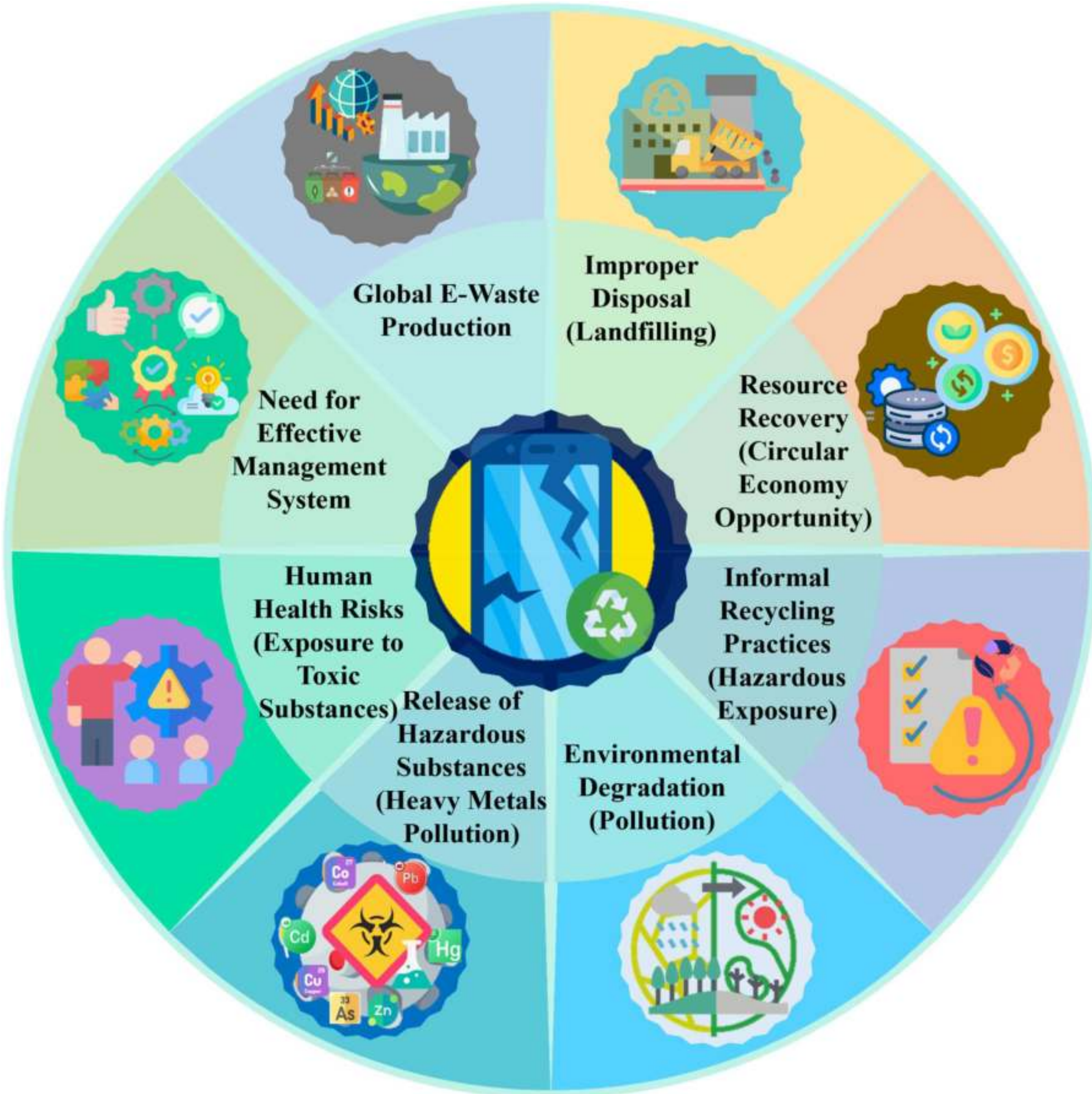

Fig. 14. Global production of e-waste.

- ➢ Hardware optimization and optimal algorithm design are essential approaches to restraining the energy consumption of AI systems [53].
- ➢ Dominating advancement in AI algorithms expands faster than the equipment performance, which increases bottlenecks. These imperfections challenge the hardware design process to catch up with AI progress [53].
- ➢ As such, accessing highly specialized hardware for AI (GPUs and TPUs) is expensive. Similarly, it curtails access to the most advanced implementations of AI, especially in the developing world and among smaller companies. This economic barrier prevents broad AI use and innovation [53].
- ➢ Scaling hardware solutions without performance degradation is a challenge for AI models, which are still growing in complexity. Research in this area continues to be crucial as developing solutions that balance algorithmic efficiency and scalability through parallelization and optimized data structures may offer potential solutions [36].
- ➢ In the case of integrating AI with IoT and Edge computing, user data stored within the edge gateway can be a matter of concern regarding data privacy and security. Compliance with regulations and safeguarding sensitive data are paramount responsibilities for deploying AI technologies [188].

These issues are appealing concerning. However, there is a means to combat them through energy-efficient AI models and the usage of new-age tech like blockchain and quantum computing with AI. With this forward-looking view, we seek not just to improve the abilities of AI but also to minimize the deficiencies in its performance.

7. Future directions

Some promising directions for developing electronic systems will be focused on quantum, neuromorphic, edge AI, AI-aided electronic design, and sustainability. Quantum computing shows great potential to transform AI applications by providing an exponential speed-up in solving problems, leading to better training of AI models and ultimately faster solution generation, Sathya said. Specific examples are already emerging in areas such as drug discovery and secure AI transactions, showcasing the wide-ranging impacts these quantum technologies could have on AI development. Here are some key takeaways from the above papers:

- ➢ The QML has been shown to enhance model performance and convergence speed, especially in drug discovery applications [189].
- ➢ This may happen in medical diagnostics because QML models, like variational quantum classifiers, can provide high accuracy with fewer computational resources [190].
- ➢ Enhancing networks using quantum will help improve the security and trustworthiness of AI transactions to solve concerns over most transactions in AI deployment [191].
- ➢ Neuromorphic computing needs to be directly addressed, which aims to develop systems that function like human brains and could improve the real-time adaptability and efficiency of artificial intelligence for tasks such as autonomous vehicles.
- ➢ To focus on edge AI advancement, especially in implementing edge AI processors to create more efficient real-time processing on small devices.
- ➢ Deep reinforcement learning is explored in this research as a functional form of quantum circuit optimization using AI, which produces more effective and better-fitting electronic solutions.
- ➢ Quantum computers will show in a new epoch in AI systems, promoting sustainability by providing faster results to its projects with much less power needed.

Quantum computing has the potential to bring significant advances; however, current limitations related to noisy quantum devices and the need for experts to design machine-learning models need to be kept in mind. As these technologies evolve, they will have a transformational role in the future of AI and electronics.

8. Conclusions

Electronics and AI have come together to create remarkable changes in many industries, including healthcare, autonomous systems, industrial automation, environmental conservation, etc. AI systems' performance and power efficiency have improved significantly, enabled by advances in hardware accelerators, quantum computers, neuromorphic computing elements, and edge AI processors. AI applications can manage vast datasets with low latency and greater scalability, thickening the soup for real-time decision-making and intelligent systems driven by new electronic systems. While such advancements are promising, there are still challenges of high energy consumption, hardware-software splits, data privacy, important costs and accessibility of AI hardware. Such hurdles impede the large-scale adoption of AI innovations, particularly in resource-limited settings. However, solutions are on the horizon, especially in the form of power-AI models, quantum computers, and edge computing advances designed for low-latency, localized processing. However, as we move forward towards a brighter future, the emergence of electronics will only gel with AI to keep on pushing innovations through different sectors. As the technologies involved in quantum computing, neuromorphic chips, and sustainable electronics continue to develop, they will lead to even more efficient and robust AI systems capable of addressing complex global challenges like climate change, healthcare and environmental preservation. Overcoming the present barriers of these technologies will be crucial for seizing their enormous potential for real-world applications so they can have a transformative influence on industries and society as a whole.

Funding

This work was supported by the College of Communication and Information Engineering, Chongqing College of Mobile Communication.

CRediT authorship contribution statement

Peng Gao: Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Muhammad Adnan:** Writing – review & editing, Writing – original draft, Supervision, Software, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors wish to thank the Alliance of International Science Organizations (ANSO) and the College of Communication and Information Engineering, Chongqing College of Mobile Communication.

Data availability

The data that has been used is confidential.

References

[1] Rekha, M., M. Rawat, and A. Singh, *IoT and Artificial Intelligence*. 2024. p. 49–62.
[2] A. Lakkshmanan, et al., Engineering applications of artificial intelligence, in: A. K. Sharma, et al. (Eds.), Enhancing Medical Imaging with Emerging Technologies, IGI Global, Hershey, PA, USA, 2024, pp. 166–179, https://doi.org/10.4018/979-8-3693-5261-8.ch010.
[3] R. Ali, H. Cui, Unleashing the potential of AI in modern healthcare: machine learning algorithms and intelligent medical robots, Res. Intell. Manuf. Assem. 3 (1) (2024) 100–108, https://doi.org/10.25082/RIMA.2024.01.002.
[4] J. Wang, The impact of artificial intelligence technology on various industries, Adv. Eng. Innov. 10 (2024) 54–63, https://doi.org/10.54254/2977-3903/10/2024103.
[5] N. Mungoli, Revolutionizing industries: the impact of artificial intelligence technologies, J. Electr. Electron. Eng. 2 (3) (2023) 206–210, https://doi.org/10.11648/j.ajai.20220601.01.
[6] V. L, A. V, Artificial intelligence in electronics and communication, Int. J. Adv. Res. Sci., Commun. Technol. (2024) 82–85, https://doi.org/10.48175/IJARSCT-18310.
[7] M.S. Sultan, M. Sultan, Advanced computation techniques for complex AI algorithms, Int. J. Sci. Res. (IJSR) 13 (2024) 934–939, https://doi.org/10.21275/SR24813223017.
[8] M.O.I. Elamin, AI through the ages: unlocking key opportunities and navigating challenges in the history and future of artificial intelligence, Int. J. Relig. 5 (12) (2024) 1152–1166, https://doi.org/10.61707/tarzcj89.
[9] G.P. Fettweis, et al., Architecture and advanced electronics pathways toward highly adaptive energy-efficient computing, Proc. IEEE 107 (1) (2018) 204–231, https://doi.org/10.1109/JPROC.2018.2874895.
[10] M. Kishani, Z. Becvar, Reducing computation, communication, and storage latency in vehicular edge computing, in: 2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring), IEEE, 2024, https://doi.org/10.1109/VTC2024-Spring62846.2024.10683495.
[11] M.M. Islam, Dynamic resource allocation for AI/ML applications in edge computing: framework architecture and optimization methods, J. Artif. Intell. Gen. Sci. (JAIGS) 3 (1) (2024) 220–234, https://doi.org/10.60087/jaigs.vol03.issue01.p65. ISSN: 3006-4023.
[12] Pasupuleti, M.K., *Advancing real-time intelligence with edge AI*. 2024. p. 94–110. doi: 10.62311/nesx/97852.
[13] A. Supriyanto, J. Santoso, Application of edge computing for RealTime data processing in smart cities, Int. J. Inf. Eng. Sci. 1 (2024) 13–18, https://doi.org/10.62951/ijies.v1i2.89.
[14] S.A.A. Wahid, A. Asad, F. Mohammadi, A survey on neuromorphic architectures for running artificial intelligence algorithms, Electronics 13 (15) (2024) 2963, https://doi.org/10.3390/electronics13152963.
[15] M. Shahsavari, et al., Advancements in spiking neural network communication and synchronization techniques for event-driven neuromorphic systems, Array 20 (2023) 100323, https://doi.org/10.1016/j.array.2023.100323.
[16] G. Ding, et al., Porous crystalline materials for memories and neuromorphic computing systems, Chem. Soc. Rev. 52 (2023), https://doi.org/10.1039/D3CS00259D.

[17] G. Ding, et al., Nanomaterials for flexible neuromorphics, Chem. Rev. 124 (2024), https://doi.org/10.1021/acs.chemrev.4c00369.
[18] I. Mondal, et al., Recent trends in neuromorphic systems for non-von Neumann in materia computing and cognitive functionalities, Appl. Phys. Rev. 11 (4) (2024), https://doi.org/10.1063/5.0220628.
[19] A. Sinicin, Overview of neuromorphic chips for artificial intelligence systems, Ekonomika Upravlenie: Problemy, Resheniya 9/9 (2024) 85–94, https://doi.org/10.36871/ek.up.p.r.2024.09.09.012.
[20] N.D. Noviati, S.D. Maulina, S. Smith, Smart grids: integrating AI for efficient renewable energy utilization, Int. Trans. Artif. Intell. 3 (1) (2024) 1–10, https://doi.org/10.33050/italic.v3i1.644.
[21] M.R. AT, et al., Intelligent energy management across smart grids deploying 6G IoT, AI, and blockchain in sustainable smart cities, IoT (2024), https://doi.org/10.3390/iot5030025.
[22] S. Dorji, et al., An extensive critique on smart grid technologies: recent advancements, key challenges, and future directions, Technologies 11 (3) (2023) 81, https://doi.org/10.3390/technologies11030081.
[23] Z. Shi, et al., Artificial intelligence techniques for stability analysis and control in smart grids: methodologies, applications, challenges and future directions, Appl. Energy 278 (2020) 115733, https://doi.org/10.1016/j.apenergy.2020.115733.
[24] S. Michael, B. Olivia, T. Sophia, Development of a smart grid system for renewable energy integration, Int. J. Mech., Electr. Civ. Eng. 1 (2) (2024) 01–07, https://doi.org/10.61132/ijmecie.v1i2.63.
[25] B. Singh, H. Singh, L.D.S. Kumar, Overview on implementation of smart grid technology, J. Eng., Manag. Inf. Technol. 2 (2024) 185–194, https://doi.org/10.61552/JEMIT.2024.04.003.
[26] K. Tunçel, Exploration and development of quantum computing algorithms for optimization, cryptography, and machine learning applications, Hum. Comput. Interact. 8 (2024) 1, https://doi.org/10.62802/1dwq2w96.
[27] K. Pandurangan, et al., Quantum-inspired algorithms for AI and machine learning. Integration of AI, Quantum Computing, and Semiconductor Technology, IGI Global, 2025, pp. 79–92, https://doi.org/10.4018/979-8-3693-7076-6.ch004.
[28] D. Chauhan, et al., Applications of quantum artificial intelligence: a systematic review, Integr. AI, Quantum Comput., Semicond. Technol. (2025) 159–182, https://doi.org/10.4018/979-8-3693-7076-6.ch008.
[29] Rani, S., et al., *Quantum machine learning: leveraging quantum computing for enhanced learning algorithms.* 2024. 6: p. 1–15. doi: 10.36948/ijfmr.2024.v06i05.27450.
[30] S. Yu, et al., Shedding light on the future: exploring quantum neural networks through optics, Adv. Quantum. Technol. (2024) 2400074, https://doi.org/10.1002/qute.202400074.
[31] C. Zhang, Foundations of Artificial Intelligence and Machine Learning, Edward Elgar Publishing eBooks, 2023.
[32] W. Shafik, Deep learning impacts in the field of artificial intelligence. Deep Learning Concepts in Operations Research, Auerbach Publications, 2024, pp. 9–26, https://doi.org/10.1201/9781003433309-2.
[33] D. Akila, et al., Significance of machine learning and deep learning in development of artificial intelligence. Multi-Criteria Decision Models in Software Reliability, CRC Press, 2022, pp. 25–44, https://doi.org/10.1201/9780367816414-2.
[34] R. Mokkapati, V.L. Dasari, A comprehensive review on areas and applications of artificial intelligence, machine learning, deep learning, and data science, in: 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), IEEE, 2023, https://doi.org/10.1109/ICIMIA60377.2023.10426237.
[35] G. Pooja, Revolutionising AI deployment: survey on hardware acceleration for machine learning optimisation and resilience, Commun. Appl. Nonlinear Anal. 31 (2024) 329–340, https://doi.org/10.52783/cana.v31.855.
[36] X. Meng, Optimization of algorithmic efficiency in AI: addressing computational complexity and scalability challenges, Appl. Comput. Eng. 45 (2024) 305–311, https://doi.org/10.54254/2755-2721/45/20241637.
[37] K. Zhang, 1.1 semiconductor industry: present & future, in: 2024 IEEE International Solid-State Circuits Conference (ISSCC), IEEE, 2024, https://doi.org/10.1109/ISSCC49657.2024.10454358.
[38] F. Zhu, P. Xu, J. Zong, Moore's law: the potential, limits, and breakthroughs, Appl. Comput. Eng. 10 (2023) 307–315, https://doi.org/10.54254/2755-2721/10/20230038.
[39] C. Richard, The future of semiconductors and electronic systems, in understanding semiconductors. Maker Innovations Series, Apress, Berkeley, CA, 2022, pp. 211–223, https://doi.org/10.1007/978-1-4842-8847-4_10.
[40] T. Pu, et al., Review of recent progress on vertical GaN-based PN diodes, Nanoscale Res. Lett. 16 (1) (2021) 101, https://doi.org/10.1186/s11671-021-03554-7.
[41] B. Grasel, J. Baptista, M. Tragner, Supraharmonic and harmonic emissions of a bi-directional V2G electric vehicle charging station and their impact to the grid impedance, Energies 15 (8) (2022) 2920, https://doi.org/10.3390/en15082920.
[42] A.M. Al-bayati, et al., A comparative design and performance study of a non-isolated DC-DC buck converter based on Si-MOSFET/Si-Diode, SiC-JFET/SiC-schottky diode, and GaN-transistor/SiC-Schottky diode power devices, in: 2017 North American Power Symposium (NAPS), IEEE, 2017, https://doi.org/10.1109/NAPS.2017.8107192.
[43] M. Gärtner, Trends in power electronics impacting E-mobility/SiC as key enabler for greener driving, in: Electronic Components and Systems for Automotive Applications: Proceedings of the 5th CESA Automotive Electronics Congress, Paris, 2018, Springer, 2019, https://doi.org/10.1007/978-3-030-14156-1_9.
[44] S. Greengard, AI Reinvents Chip Design, ACM, New York, NY, USA, 2024, https://doi.org/10.1145/3673645.
[45] X. Zhao, Analysis of the impact of artificial intelligence technology on the development of integrated circuits, Appl. Comput. Eng. 73 (2024) 160–164, https://doi.org/10.54254/2755-2721/73/20240387.
[46] S.K. Pullabhatla, P.B. Bobba, S. Yadlapalli, Comparison of GAN, SIC, SI technology for high frequency and high efficiency inverters, in: E3S Web of Conferences, EDP Sciences, 2020, https://doi.org/10.1051/e3sconf/202018401012.
[47] S. Musumeci, V. Barba, Gallium nitride power devices in power electronics applications: state of art and perspectives, Energies 16 (9) (2023) 3894, https://doi.org/10.3390/en16093894.
[48] H. Peng, et al., Evaluating emerging AI/ML accelerators: IPU, RDU, and NVIDIA/AMD GPUs, in: Companion of the 15th ACM/SPEC International Conference on Performance Engineering, 2024, https://doi.org/10.1145/3629527.3651428.
[49] S. Pfenning, et al., Analysis of embedded GPU architectures for AI in neuromuscular applications, IADIS Int. J. Comput. Sci. Inf. Syst. (2024), https://doi.org/10.33965/ijcsis_2024190101.
[50] B. Schmidt, A. Hildebrandt, From GPUs to AI and quantum: three waves of acceleration in bioinformatics, Drug Discov. Today 29 (6) (2024) 103990, https://doi.org/10.1016/j.drudis.2024.103990.
[51] N. Gupta, Introduction to hardware accelerator systems for artificial intelligence and machine learning. Advances in Computers, Elsevier, 2021, pp. 1–21, https://doi.org/10.1016/bs.adcom.2020.07.001.
[52] P. Altoe, Processing units in the age of AI, in: Proceedings of the 21st ACM International Conference on Computing Frontiers, 2024, https://doi.org/10.1145/3649153.3660496.
[53] W. Hou, Exploring the horizon of AI development: navigating constraints of chips and power in the technological landscape, Appl. Comput. Eng. 77 (2024) 177–182, https://doi.org/10.54254/2755-2721/77/20240688.
[54] S. Kumar, S. Simran, M. Singh, Quantum intelligence: merging AI and quantum computing for unprecedented power, in: 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies, IEEE, 2024, https://doi.org/10.1109/TQCEBT59414.2024.10545163.
[55] Chen, K.-C., et al., *Multi-GPU-enabled hybrid quantum-classical workflow in quantum-HPC middleware: applications in quantum simulations*. 2024. doi: https://doi.org/10.48550/arXiv.2403.05828.
[56] Kharel, S.R., et al., *Automated and Holistic Co-design of Neural Networks and ASICs for Enabling In-Pixel Intelligence.* arXiv preprint arXiv:2407.14560, 2024. doi: https://doi.org/10.48550/arXiv.2407.14560.
[57] Elbtity, M., P. Chandarana, and R. Zand, *Flex-TPU: A Flexible TPU with Runtime Reconfigurable Dataflow Architecture.* arXiv preprint arXiv:2407.08700, 2024. doi: https://doi.org/10.48550/arXiv.2407.08700.
[58] Carrión, D.S. and V. Prohaska, *Exploration of TPUs for AI Applications.* arXiv preprint arXiv:2309.08918, 2023. doi: https://doi.org/10.48550/arXiv.2309.08918.
[59] Silvano, C., et al., *A survey on deep learning hardware accelerators for heterogeneous HPC platforms.* arXiv preprint arXiv:2306.15552, 2023. doi: https://doi.org/10.48550/arXiv.2306.15552.
[60] C. Zou, Revolutionizing machine learning: harnessing hardware accelerators for enhanced AI efficiency, Appl. Comput. Eng. 47 (2024) 141–146, https://doi.org/10.54254/2755-2721/47/20241256.
[61] H. Lu, FPGA-based Vit inference accelerator optimization, Highlights Sci., Eng. Technol. 111 (2024) 282–287, https://doi.org/10.54097/ffw9q577.
[62] T.-K. Chi, et al., An edge computing system with AMD Xilinx FPGA AI customer platform for advanced driver assistance system, Sensors 24 (10) (2024) 3098, https://doi.org/10.3390/s24103098.
[63] L.G. Leon-Vega, E. Obregon-Fonseca, J. Castro-Godinez, A user-friendly ecosystem for AI FPGA-based accelerators, in: 2024 IEEE International Conference on Omni-layer Intelligent Systems (COINS), IEEE, 2024, https://doi.org/10.1109/COINS61597.2024.10622147.
[64] K. Khalil, et al., Efficient hardware implementation of artificial neural networks on FPGA, in: 2024 IEEE 6th International Conference on AI Circuits and Systems (AICAS), IEEE, 2024, https://doi.org/10.1109/AICAS59952.2024.10595867.
[65] S. Dhull, et al., Energy-efficient neural network using an anisotropy field gradient-based self-resetting neuron and meander synapse, Appl. Phys. Lett. 125 (1) (2024), https://doi.org/10.1063/5.0220809.
[66] B. Tossoun, et al., Large-scale integrated photonics for energy-efficient AI hardware, in: 2024 IEEE Photonics Society Summer Topicals Meeting Series (SUM), IEEE, 2024, https://doi.org/10.1109/SUM60964.2024.10614557.
[67] A. Lbath, I. Labriji, Energy efficiency in AI for 5G and beyond: a DeepRx case study, in: 2024 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit), IEEE, 2024, https://doi.org/10.1109/EuCNC/6GSummit60053.2024.10597065.
[68] S. Rajput, T. Sharma, Benchmarking emerging deep learning quantization methods for energy efficiency, in: 2024 IEEE 21st International Conference on Software Architecture Companion (ICSA-C), IEEE, 2024, https://doi.org/10.1109/ICSA-C63560.2024.00049.
[69] B. Venu, et al., Negative capacitance FET 8T SRAM computing in-memory based logic design for energy efficient AI edge devices, in: 2024 IEEE International Symposium on Circuits and Systems (ISCAS), IEEE, 2024, https://doi.org/10.1109/ISCAS58744.2024.10558683.
[70] Q. Wang, et al., Environmental data and facts in the semiconductor manufacturing industry: an unexpected high water and energy consumption situation, Water Cycle 4 (2023) 47–54, https://doi.org/10.1016/j.watcyc.2023.01.004.

[71] B. Gopalakrishnan, Y. Mardikar, D. Korakakis, Energy analysis in semiconductor manufacturing, Energy Eng. 107 (2) (2010) 6–40, https://doi.org/10.1080/01998591009709867.

[72] K. Frost, I. Hua, A spatially explicit assessment of water use by the global semiconductor industry, in: 2017 IEEE Conference on Technologies for Sustainability (SusTech), IEEE, 2017, https://doi.org/10.1109/SusTech.2017.8333525.

[73] Bong, P., M.A. Malek, and Z. Noor, *A review on water footprint assessment and water-food-energy nexus for electronic and food products.* 2018. doi: 10.14419/ijet.v7i4.28.22321.

[74] K. Ukoba, et al., Optimizing renewable energy systems through artificial intelligence: review and future prospects, Energy Environ. (2024) 35–37, https://doi.org/10.1177/0958305X241256293.

[75] A. Darwish, et al., Artificial intelligence for sustainable energy transition: optimising renewable energy integration and management, ARID Int. J. Sci. Technol. (2024) 55–79, https://doi.org/10.36772/arid.aijst.2024.7134.

[76] A. Bennagi, et al., Comprehensive study of the artificial intelligence applied in renewable energy, Energy Strategy Rev. 54 (2024) 101446, https://doi.org/10.1016/j.esr.2024.101446.

[77] L.A. Yousef, H. Yousef, L. Rocha-Meneses, Artificial intelligence for management of variable renewable energy systems: a review of current status and future directions, Energies 16 (24) (2023) 8057, https://doi.org/10.3390/en16248057.

[78] N. Mohamed, Renewable energy in the age of AI: cybersecurity challenges and opportunities, in: 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, 2024, https://doi.org/10.1109/ICCCNT61001.2024.10724383.

[79] Z. Allal, et al., Machine learning solutions for renewable energy systems: applications, challenges, limitations, and future directions, J. Environ. Manag. 354 (2024) 120392, https://doi.org/10.1016/j.jenvman.2024.120392.

[80] M. Adnan, et al., Known and unknown environmental impacts related to climate changes in Pakistan: an under-recognized risk to local communities, Sustainability 16 (14) (2024) 6108, https://doi.org/10.3390/su16146108.

[81] M. Shao, et al., Carbonate mineral dissolution and its carbon sink effect in Chinese loess, Land 12 (1) (2023) 133, https://doi.org/10.3390/land12010133.

[82] M. Adnan, et al., Addressing current climate issues in Pakistan: an opportunity for a sustainable future, Environ. Chall. 15 (2024) 100887, https://doi.org/10.1016/j.envc.2024.100887.

[83] J. Huo, C. Peng, Depletion of natural resources and environmental quality: prospects of energy use, energy imports, and economic growth hindrances, Resour. Policy 86 (2023) 104049, https://doi.org/10.1016/j.resourpol.2023.104049.

[84] A. Pfenning-Butterworth, et al., Interconnecting global threats: climate change, biodiversity loss, and infectious diseases, Lancet Planet. Health 8 (4) (2024) e270–e283, https://doi.org/10.1016/S2542-5196(24)00021-4.

[85] M. Adnan, et al., Human inventions and its environmental challenges, especially artificial intelligence: new challenges require new thinking, Environ. Chall. 16 (2024) 100976, https://doi.org/10.1016/j.envc.2024.100976.

[86] H.M. Deitel, B. Deitel, 2—The evolution of computers, in: H.M. Deitel, B. Deitel (Eds.), Study Guide to Accompany Computer and Data Processing, Academic Press, 1985, pp. 11–22, https://doi.org/10.1016/B978-0-12-209005-9.50007-2.

[87] L. Dadda, The evolution of computer architectures, in: [1991]Proceedings, Advanced Computer Technology, Reliable Systems and Applications, 1991, https://doi.org/10.1109/CMPEUR.1991.257347.

[88] Y. Jin, Current status and future development of quantum computing, Theor. Nat. Sci. 36 (2024) 165–174, https://doi.org/10.54254/2753-8818/36/20240606.

[89] A. Lohia, Quantum artificial intelligence: enhancing machine learning with quantum computing, J. Quantum Sci. Technol. 1 (2) (2024) 6–11, https://doi.org/10.36676/jqst.v1.i2.9.

[90] Ho, K.T.M., et al., *Quantum computing for climate resilience and sustainability challenges.* arXiv preprint arXiv:2407.16296, 2024. doi: https://doi.org/10.48550/arXiv.2407.16296.

[91] O. Fernandes, et al., Quantum computers and their application in future era, Int. J. Adv. Res. Sci., Commun. Technol. (2024) 227–230, https://doi.org/10.48175/ijarsct-19331.

[92] M. Mittal, Quantum computing and information: recent developments and future prospects, J. Quantum Sci. Technol. 1 (2) (2024) 12–17, https://doi.org/10.36676/jqst.v1.i2.10.

[93] S.A.A. Wahid, A. Asad, F. Mohammadi, A survey on neuromorphic architectures for running artificial intelligence algorithms, Electronics 13 (15) (2024) 2963, https://doi.org/10.3390/electronics13152963.

[94] X. Hu, et al., Neuromorphic computing using a floating gate modulated photoelectric synaptic transistor, Laser Photon. Rev. 18 (12) (2024), https://doi.org/10.1002/lpor.202400319.

[95] Karki, S., et al., *Neuromorphic on-chip reservoir computing with spiking neural network architectures.* arXiv preprint arXiv:2407.20547, 2024. doi: https://doi.org/10.48550/arXiv.2407.20547.

[96] J. Hu, et al., Reconfigurable neuromorphic computing with 2D material heterostructures for versatile neural information processing, Nano Lett. 24 (30) (2024) 9391–9398, https://doi.org/10.1021/acs.nanolett.4c02658.

[97] Patil, C.A., *The Race For AI Semiconductor Chips.* https://www.chetanpatil.in/the-race-for-ai-semiconductor-chips/. 2020.

[98] S.K. Addepalli, V. Jyothi, A.H. Poojari, Systems and Methods for Artificial Intelligence Hardware Processing, Google Patents, 2020.

[99] J.R. Hu, et al., Systematic co-optimization from chip design, process technology to systems for GPU AI chip, in: 2018 International Symposium on VLSI Design, Automation and Test (VLSI-DAT), IEEE, 2018, https://doi.org/10.1109/VLSI-DAT.2018.8373280.

[100] X. Li, Analysis of the designs and applications of AI chip, Highlights Sci., Eng. Technol. 76 (2023) 168–180, https://doi.org/10.54097/k1p7yk27.

[101] K. Penev, et al., Energy efficiency evaluation of artificial intelligence algorithms, Electronics 13 (19) (2024) 3836, https://doi.org/10.3390/electronics13193836.

[102] X. Shen, et al., Artificial intelligence applications in high-frequency magnetic components design for power electronics systems: an overview, IEEE Trans. Power. Electron. (2024), https://doi.org/10.1109/TPEL.2024.3381431.

[103] A. Arya, et al., Investigation into designing VLSI of a flexible architecture for a deep neural network accelerator, J. Electr. Syst. 20 (6s) (2024) 1024–1031, https://doi.org/10.52783/jes.2834.

[104] Y. Zhao, F. Jain, L. Wang, An in-memory-computing structure with quantum-dot transistor toward neural network applications: from analog circuits to memory arrays, Int. J. High Speed Electron. Syst. 33 (02n03) (2024) 2440059, https://doi.org/10.1142/S0129156424400597.

[105] N. Varatharajan, et al., Deep learning: overview, applications and computing devices. Deep Learning Concepts in Operations Research, 2024, pp. 1–8.

[106] S. Wang, K. Xu, Z. Ling, Deep learning-based chip power prediction and optimization: an intelligent EDA approach, Int. J. Innov. Res. Comput. Sci. Technol. 12 (4) (2024) 77–87, https://doi.org/10.55524/ijircst.2024.12.4.13.

[107] N. Kaushik, A. Gill, R. Raghavendra, Frontiers of artificial intelligence through accelerated model training and optimization techniques, in: 2024 IEEE 13th International Conference on Communication Systems and Network Technologies (CSNT), IEEE, 2024, https://doi.org/10.1109/CSNT60213.2024.10545807.

[108] T. Ahmad, et al., Artificial intelligence in sustainable energy industry: status quo, challenges and opportunities, J. Clean. Prod. 289 (2021) 125834, https://doi.org/10.1016/j.jclepro.2021.125834.

[109] G. Papyshev, M. Yarime, The state's role in governing artificial intelligence: development, control, and promotion through national strategies, Policy Des. Pract. 6 (1) (2023) 79–102, https://doi.org/10.1080/25741292.2022.2162252.

[110] H. Androshchuk, Policies and strategies for the development of artificial intelligence in the countries of the world: quo vadis?(part 2), Sci., Technol., Innov. 2 (2023) 26, https://doi.org/10.35668/2520-6524-2023-1-03.

[111] S. Wang, et al., Distributed high-performance computing methods for accelerating deep learning training, J. Knowl. Learn. Sci. Technol. 3 (3) (2024) 108–126, https://doi.org/10.60087/jklst.v3.n3.p108-126. ISSN: 2959-6386 (online).

[112] Gershon, T., et al., *The infrastructure powering IBM's Gen AI model development.* arXiv preprint arXiv:2407.05467, 2024. doi: 10.48550/arXiv.2407.05467.

[113] L. Zeng, et al., Implementation of big AI models for wireless networks with collaborative edge computing, IEEE Wirel. Commun. 31 (3) (2024) 50–58, https://doi.org/10.48550/arXiv.2404.17766.

[114] K. Gao, et al., Accelerating distributed model training through intelligent node selection and data allocation strategies in 6G network, in: 2024 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE, 2024, https://doi.org/10.1109/ICCWorkshops59551.2024.10615801.

[115] R. Wang, et al., Poster: flexible scheduling of network and computing resources for distributed AI tasks, in: Proceedings of the ACM SIGCOMM 2024 Conference: Posters and Demos, 2024, https://doi.org/10.1145/3672202.3673744.

[116] K. Kim, M.-j. Park, Present and future, challenges of high bandwith memory (HBM), in: 2024 IEEE International Memory Workshop (IMW), IEEE, 2024, https://doi.org/10.1109/IMW59701.2024.10536972.

[117] A. Chen, et al., Emerging nonvolatile memories for analog neuromorphic computing, in: Electrochemical Society Meeting Abstracts 245, The Electrochemical Society, Inc, 2024, https://doi.org/10.1149/MA2024-01211293mtgabs.

[118] S. Pandey, P.R. Panda, NeuroTAP: thermal and memory access pattern-aware data mapping on 3D DRAM for maximizing DNN performance, ACM Trans. Embed. Comput. Syst. 23 (6) (2024) 1–30, https://doi.org/10.1145/367717.

[119] Y. Xu, R. Han, J. Ouyang, Memory relevant hyperparameters optimization for DNN training at edge, in: 2024 IEEE 4th International Conference on Electronic Technology, Communication and Information (ICETCI), IEEE, 2024, https://doi.org/10.1109/ICETCI61221.2024.10594490.

[120] D. Pandey, EdgeAI: revolutionizing real-time intelligence at the network periphery, Int. J. Res. Appl. Sci. Eng. Technol. 12 (2024) 203–212, https://doi.org/10.22214/ijraset.2024.63875.

[121] D. R, V. L, Edge AI based object detection system using TFLite, Int. J. Sci. Res. Eng. Manag. 08 (2024) 1–9.

[122] S. Alam, et al., Survey of deep learning accelerators for edge and emerging computing, Electronics 13 (15) (2024) 2988, https://doi.org/10.3390/electronics13152988.

[123] D.K. Vaka, The convergence of AI, ML, and IoT in automotive systems: a future perspective on edge computing, Int. J. Eng. Comput. Sci. 11 (2024) 25535–25549, https://doi.org/10.18535/ijecs/v11i05.4673.

[124] S.S. Gill, et al., Edge AI: a taxonomy, systematic review and future directions, Clust. Comput. 28 (1) (2025) 1–53, https://doi.org/10.1007/s10586-024-04686-y.

[125] Z. Shang, et al., Artificial intelligence, the digital surgeon: unravelling its emerging footprint in healthcare–the narrative review, J. Multidiscip. Healthc. (2024) 4011–4022, https://doi.org/10.2147/JMDH.S482757.

[126] T. Khinvasara, K.M. Cuthrell, N. Tzenios, Harnessing artificial intelligence in healthcare analytics: from diagnosis to treatment optimization, Asian J. Med. Health 22 (8) (2024) 15–31, https://doi.org/10.9734/ajmah/2024/v22i81066.

[127] P. Laxmi, Neuromorphic computing: innovations and future prospects, Int. J. Adv. Res. Sci., Commun. Technol. (2024) 397–400, https://doi.org/10.48175/IJARSCT-19435.

[128] T. Li, Neuromorphic devices based on two-dimensional materials and their applications, Highlights Sci., Eng. Technol. 87 (2024) 186–191, https://doi.org/10.54097/kxsmsn90.

[129] V. Sehrawat, Quantum computing: algorithms and applications in optimization problems, J. Quantum Sci. Technol. 1 (2) (2024) 18–22, https://doi.org/10.36676/jqst.v1.i2.11.

[130] S. Hadap, M. Patil, Quantum computing in artificial intelligence: a paradigm shift, Int. J. Adv. Res. Sci., Commun. Technol. (2024) 530–534, https://doi.org/10.48175/IJARSCT-18957.

[131] А.А. Волкорез, Е.В. Ширинкина, Quantum artificial intelligence as a technology capable of changing markets and business models, J. Monet. Econ. Manag. (2024) 83–88, https://doi.org/10.26118/2782-4586.2024.91.63.012.

[132] S. Goyal, et al., Quantum computing in the era of IoT: revolutionizing data processing and security in connected devices. Applied Data Science and Smart Systems, CRC Press, 2024, pp. 552–559, https://doi.org/10.1201/9781003471059-70.

[133] Omidsajedi, S.N., et al., *Latency optimized deep neural networks (DNNs): an artificial intelligence approach at the edge using multiprocessor system on chip (MPSoC).* arXiv preprint arXiv:2407.18264, 2024. doi: https://doi.org/10.48550/arXiv.2407.18264.

[134] Y. Shahzad, et al., Internet of energy: opportunities, applications, architectures and challenges in smart industries, Comput. Electr. Eng. 86 (2020) 106739, https://doi.org/10.1016/j.compeleceng.2020.106739.

[135] A.W. Colombo, et al., A 70-year industrial electronics society evolution through industrial revolutions: the rise and flourishing of information and communication technologies, IEEE Ind. Electron. Mag. 15 (1) (2021) 115–126, https://doi.org/10.1109/MIE.2020.3028058.

[136] P. Zahariev, et al., Industry 4.0 and beyond—present trends, emerging solutions and future technologies in the area of the industrial automation, in: 2024 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), IEEE, 2024, https://doi.org/10.1109/ECTIDAMTNCON60518.2024.10479988.

[137] H.O. Omoregbee, M.U. Olanipekun, Exploring the intelligent attributes of industrial 4.0: the next revolution and beyond, in: International Conference on Intelligent and Innovative Computing Applications, 2022, pp. 30–39, https://doi.org/10.59200/ICONIC.2022.004.

[138] J. Rymarczyk, The change in the traditional paradigm of production under the influence of industrial revolution 4.0, Businesses 2 (2) (2022) 188–200, https://doi.org/10.3390/businesses2020013.

[139] T. Moloi, T. Marwala, The fourth industrial revolution. Enterprise Risk Management in the Fourth Industrial Revolution, Springer, 2023, pp. 11–20, https://doi.org/10.1007/978-981-99-6307-2.

[140] Pasricha, S., *Optical computing for deep neural network acceleration: foundations, recent developments, and emerging directions.* arXiv preprint arXiv:2407.21184, 2024. doi: https://doi.org/10.48550/arXiv.2407.21184.

[141] L. De Marinis, et al., Photonic technologies for analog neuromorphic computing, in: 2024 IEEE Photonics Society Summer Topicals Meeting Series (SUM), IEEE, 2024, https://doi.org/10.1109/SUM60964.2024.10614512.

[142] J. Zhou, et al., High-speed energy efficient optics for AI/ML applications, in: 2024 IEEE Photonics Society Summer Topicals Meeting Series (SUM), IEEE, 2024, https://doi.org/10.1109/SUM60964.2024.10614550.

[143] Rausell-Campo, J.R., et al., *Programmable photonic extreme learning machines.* arXiv preprint arXiv:2407.03218, 2024. https://doi.org/10.48550/arXiv.2407.03218.

[144] D.V. Vegesna, AI-powered mental health monitoring using wearable devices and mobile sensing, Int. Res. J. Comput. Sci. 11 (2024) 545–550, https://doi.org/10.26562/irjcs.2024.v1108.01.

[145] J. Gu, AI-empowered neural processing for intelligent human-machine interface and biomedical devices, Open Access Gov. 43 (2024) 268–269, https://doi.org/10.56367/OAG-043-11463.

[146] M. Aldergham, A. Alfouri, R.A. Madat, Artificial intelligence in medicine, South East Eur. J. Public Health (2024) 774–790, https://doi.org/10.70135/seejph.vi.1561.

[147] S. Gupta, V. Kumar, P. Gupta, Role of artificial intelligence in health sector. Challenges in Information, Communication and Computing Technology, CRC Press, 2025, pp. 690–695, https://doi.org/10.1201/9781003559092-119.

[148] C.S. Jothi, et al., Revolutionizing healthcare through robotics and AI integration: a comprehensive approach. Exploring the Micro World of Robotics Through Insect Robots, IGI Global, 2025, pp. 213–234, https://doi.org/10.4018/979-8-3693-6150-4.ch011.

[149] V.-T. Nguyen, et al., Development of a wearable device for heart rate monitoring and fall detection using machine learning to analyze and detect early anomaly of cardiovascular conditions, Tạp chí Khoa học và Công nghệ-Đại học Đà Nẵng (2024) 7–12, https://doi.org/10.31130/ud-jst.2024.158ICT.

[150] M. Constantinides, et al., Good intentions, risky inventions: a method for assessing the risks and benefits of AI in mobile and wearable uses, Proc. ACM. Hum. Comput. Interact. 8 (MHCI) (2024) 1–28, https://doi.org/10.48550/arXiv.2407.09322.

[151] S. Sen, A. Datta, Human-inspired distributed wearable AI, in: Proceedings of the 61st ACM/IEEE Design Automation Conference, 2024, https://doi.org/10.48550/arXiv.2406.18791.

[152] W. Fabre, et al., From near-sensor to in-sensor: a state-of-the-art review of embedded AI vision systems, Sensors 24 (16) (2024) 5446, https://doi.org/10.3390/s24165446.

[153] L. Chen, et al., AI-driven sensing technology: review, Sensors 24 (10) (2024) 2958, https://doi.org/10.3390/s24102958.

[154] M. Kozłowski, S. Racewicz, S. Wierzbicki, Image analysis in autonomous vehicles: a review of the latest AI solutions and their comparison, Appl. Sci. 14 (18) (2024) 8150, https://doi.org/10.3390/app14188150.

[155] A. Thakur, S.K. Mishra, An in-depth evaluation of deep learning-enabled adaptive approaches for detecting obstacles using sensor-fused data in autonomous vehicles, Eng. Appl. Artif. Intell. 133 (2024) 108550, https://doi.org/10.1016/j.engappai.2024.108550.

[156] R.R. Lamsal, A. Devkota, M.S. Bhusal, Navigating global challenges: the crucial role of semiconductors in advancing globalization, J. Inst. Eng. (India): Ser. B 104 (6) (2023) 1389–1399, https://doi.org/10.1007/s40031-023-00938-4.

[157] S. Alam, et al., Globality and complexity of the semiconductor ecosystem. AccentGlob. Semicond. Alliance, 2020. https://www.gsaglobal.org/wp-content/uploads/2020/02/GSA-Accenture-Globality-and-Complexity-of-the-Semiconductor-Ecosystem.pdf.

[158] M. Ieong, Semiconductor industry driven by applications: artificial intelligence and internet-of-things, in: 2018 IEEE International Conference on Electron Devices and Solid State Circuits (EDSSC), IEEE, 2018, https://doi.org/10.1109/EDSSC.2018.8487118.

[159] A. Al Tareq, et al., Impact of IoT and embedded system on semiconductor industry a case study, Control Syst. Optim. Lett. 2 (2) (2024) 211–216, https://doi.org/10.59247/csol.v2i2.111.

[160] Haramboure, A., et al., *Vulnerabilities in the semiconductor supply chain.* 35 p, 18151965. 2023. doi: https://doi.org/10.1787/6bed616f-en.

[161] S.M. Khan, A. Mann, D. Peterson, The semiconductor supply chain: assessing national competitiveness, Cent. Secur. Emerg. Technol. 8 (8) (2021) 1–98, https://doi.org/10.51593/20190016.

[162] J. Lladós Masllorens, A.M. Artola, J. Vilaseca Requena, La cadena global de valor en la industria electrónica, Investig. Econ. 77 (304) (2018) 135–170, https://doi.org/10.22201/fe.01851667p.2018.304.66402.

[163] A. Antonenko, V. Boretskij, O. Zagaria, Classification of indoor air pollution using low-cost sensors by machine learning, in: EGU General Assembly Conference Abstracts, 2023, https://doi.org/10.5194/egusphere-egu23-14856.

[164] T.-D. Hoang, et al., Artificial intelligence in pollution control and management: status and future prospects. Artificial Intelligence and Environmental Sustainability: Challenges and Solutions in the Era of Industry 4.0, 2022, pp. 23–43, https://doi.org/10.1007/978-981-19-1434-8_2.

[165] A. Albahri, et al., A systematic review of trustworthy artificial intelligence applications in natural disasters, Comput. Electr. Eng. 118 (2024) 109409, https://doi.org/10.1016/j.compeleceng.2024.109409.

[166] A. Chakrabarty, S. Nandi, Electronic waste vulnerability: circular economy as a strategic solution, Clean. Technol. Environ. Policy 23 (2) (2021) 429–443, https://doi.org/10.1007/s10098-020-01976-y.

[167] V. Forti, et al., The Global E-Waste Monitor 2020, 120, United Nations University (UNU), International Telecommunication Union (ITU) & International Solid Waste Association (ISWA), Bonn/Geneva/Rotterdam, 2020, 978-92-808-9114-0.

[168] H. Schandl, et al., Shared socio-economic pathways and their implications for global materials use, Resour., Conserv. Recycl. 160 (2020) 104866, https://doi.org/10.1016/j.resconrec.2020.104866.

[169] L. Mancini, P. Nuss, Responsible materials management for a resource-efficient and low-carbon society, Resources 9 (6) (2020) 68, https://doi.org/10.3390/resources9060068.

[170] E.A. Olivetti, J.M. Cullen, Toward a sustainable materials system, Science 360 (6396) (2018) 1396–1398, https://doi.org/10.1126/science.aat682.

[171] L. Andeobu, S. Wibowo, S. Grandhi, Artificial intelligence applications for sustainable solid waste management practices in Australia: a systematic review, Sci. Total Environ. 834 (2022) 155389, https://doi.org/10.1016/j.scitotenv.2022.155389.

[172] S.L. Nañez Alonso, et al., Digitalization, circular economy and environmental sustainability: the application of artificial intelligence in the efficient self-management of waste, Sustainability 13 (4) (2021) 2092, https://doi.org/10.3390/su13042092.

[173] X. An, et al., Natural factors of microplastics distribution and migration in water: a review, Water 16 (11) (2024) 1595, https://doi.org/10.3390/w16111595.

[174] M. Titirici, et al., The sustainable materials roadmap, J. Phys. 5 (3) (2022) 032001, https://doi.org/10.1088/2515-7639/ac4ee5.

[175] Attard-Frost, B. and D.G. Widder, *The Ethics of AI Value Chains.* arXiv preprint arXiv:2307.16787, 2023. doi: https://doi.org/10.48550/arXiv.2307.16787.

[176] G. Zhao, et al., Risk analysis of the agri-food supply chain: a multi-method approach, Int. J. Prod. Res. 58 (16) (2020) 4851–4876, https://doi.org/10.1080/00207543.2020.1725684.

[177] R. Akram, et al., Considering natural gas rents, mineral rents, mineral depletion, and natural resources depletion as new determinants of sustainable development, Resour. Policy 96 (2024) 105200, https://doi.org/10.1016/j.resourpol.2024.105200.

[178] F. Chen, et al., Resource depletion and conservation: balancing demands on resources for green recovery and sustainability, Resour. Policy 89 (2024) 104544, https://doi.org/10.1016/j.resourpol.2023.104544.

[179] K. Dhivya, G. Premalatha, E-waste challenges & solutions, Sustain. Manag. Electron. Waste (2024) 255–275, https://doi.org/10.1002/9781394166923.ch13.

[180] R. Kumar, et al., Environmental impacts of E-waste: pollution and resource depletion. Sustainable Solutions for E-Waste and Development, IGI Global, 2024, pp. 12–32, https://doi.org/10.4018/979-8-3693-1018-2.ch002.

[181] M.U. Ali, et al., Silent threats of lead-based paints in toys and households to children's health and development, J. Hazard. Mater. (2024) 136984, https://doi.org/10.1016/j.jhazmat.2024.136984.
[182] B. Fang, et al., Artificial intelligence for waste management in smart cities: a review, Environ. Chem. Lett. 21 (4) (2023) 1959–1989, https://doi.org/10.1007/s10311-023-01604-3.
[183] L.K. Bhardwaj, P. Rath, R. Tokas, E-waste management in developing countries: current practices, challenges, disposal, and impact on human health and environment. Sustainable Solutions for E-Waste and Development, 2024, pp. 90–102, https://doi.org/10.20944/preprints202312.0582.v1.
[184] A. Shreyas Madhav, et al., Application of artificial intelligence to enhance collection of E-waste: a potential solution for household WEEE collection and segregation in India, Waste Manag. Res. 40 (7) (2022) 1047–1053, https://doi.org/10.1177/0734242X211052846.
[185] S. Goyal, et al., E-waste: promoting the need for green electronics, in: 2023 International Conference on Power Energy, Environment & Intelligent Control (PEEIC), IEEE, 2023, https://doi.org/10.1109/PEEIC59336.2023.10451991.
[186] Chou, S.-K., et al., *The Energy Cost of Artificial Intelligence of Things Lifecycle*. 2024. doi: https://doi.org/10.48550/arXiv.2408.00540.
[187] Goel, P., *AI for Energy Efficiency and Conservation*. 2024. p. 32–49. doi: 10.4018/979-8-3693-6567-0.ch003.
[188] Zhang, L., et al., *Quantum Long Short-Term Memory for Drug Discovery*. 2024. doi: https://doi.org/10.48550/arXiv.2407.19852.
[189] Saha, P., *Quantum Machine Learning with Application to Progressive Supranuclear Palsy Network Classification*. 2024. doi: https://doi.org/10.48550/arXiv.2407.06226.
[190] S. Jagan, et al., Quantum technology improves small-world network collective dynamics for secure AI transactions. Quantum Networks and Their Applications in AI, 2024, pp. 114–127, https://doi.org/10.4018/979-8-3693-5832-0.ch008.
[191] Dai, X., et al., *Quantum Machine Learning Architecture Search via Deep Reinforcement Learning*. 2024. doi: https://doi.org/10.48550/arXiv.2407.20147.