Neurocomputing 599 (2024) 128096

Contents lists available at ScienceDirect

Neurocomputing

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

A review of green artificial intelligence: Towards a more sustainable future

Verónica Bolón-Canedo *, Laura Morán-Fernández, Brais Cancela, Amparo Alonso-Betanzos

CITIC, Universidade da Coruña, A Coruña, Spain

ARTICLE INFO

Keywords:
Green machine learning
Sustainability
Green-by AI
Green-in AI

ABSTRACT

Green artificial intelligence (AI) is more environmentally friendly and inclusive than conventional AI, as it not only produces accurate results without increasing the computational cost but also ensures that any researcher with a laptop can perform high-quality research without the need for costly cloud servers. This paper discusses green AI as a pivotal approach to enhancing the environmental sustainability of AI systems. Described are AI solutions for eco-friendly practices in other fields (green-by AI), strategies for designing energy-efficient machine learning (ML) algorithms and models (green-in AI), and tools for accurately measuring and optimizing energy consumption. Also examined are the role of regulations in promoting green AI and future directions for sustainable ML. Underscored is the importance of aligning AI practices with environmental considerations, fostering a more eco-conscious and energy-efficient future for AI systems.

1. Introduction

Over the past few years, artificial intelligence (AI) and machine learning (ML) have brought about a revolution in numerous industries, greatly enhancing efficiency and accuracy in sectors like healthcare, finance, transportation, education, entertainment, etc. To achieve better performance, ML models have had to become increasingly complex, resulting in larger numbers of parameters to estimate. However, these advances come at a cost, as the resource requirements to train and run these models has risen significantly. As can be seen in Fig. 1,[1] training modern ML models requires vast amounts of computational resources, and of energy and water for the refrigeration of the data centers housing immense volumes of training data.

While the trend in the last decade has been towards exponential growth in data demands and greater numbers of hyperparameters, this trend has not been reflected in model accuracy improvements. Yet AI, by fostering sustainable and efficient solutions, holds immense potential for countries' transition to clean and sustainable practices. To achieve this, several sustainability measurements need to be made that increase the transparency of model results not only in performance and accuracy, but also in the carbon footprint, reflecting energy and water consumption (e.g., using an ML emissions calculator[2]). This energy consumption is projected to potentially reach over 30% of the world's total energy consumption by 2030.[3] Large language models (LLMs), such as the recently launched ChatGPT (with GPT-4 as the backbone model) aggravate this trend with their substantial energy requirements. Some authors [1] have estimated that training GPT-3 on a database of 500 billion words required 1287 MWh of electricity and 10,000 computer chips, equivalent to the energy needed to power around 121 homes for a year in the USA. Furthermore, this training produced around 550 tons of carbon dioxide, equivalent to flying 33 times from Australia to the UK. Since the subsequent version, GPT-4, was trained on 570 times more parameters than GPT-3, it undoubtedly required even more energy. The environmental cost is not restricted to training, as using these systems also has a cost. As an example, GPT-3 was accessed 590 million times in January 2023, leading to energy consumption equivalent to that of 175,000 persons.[4] Moreover, in inference time, each ChatGPT query consumes energy equivalent to running a 5 W LED bulb for 1hr 20 min, representing 260.42 MWh per day.

With the environmental impact of this disruptive technology growing almost exponentially, serious concerns about its carbon footprint have led to a new paradigm, called green AI, which incorporates sustainable practices and techniques in model design, training, and deployment that aim to reduce the associated environmental cost and carbon footprint.

* Corresponding author.
E-mail addresses: veronica.bolon@udc.es (V. Bolón-Canedo), laura.moranf@udc.es (L. Morán-Fernández), brais.cancela@udc.es (B. Cancela), amparo.alonso.betanzos@udc.es (A. Alonso-Betanzos).

[1] https://aiindex.stanford.edu/report/
[2] https://mlco2.github.io/impact/#compute
[3] https://www.ll.mit.edu/news/ai-models-are-devouring-energy-tools-reduce-consumption-are-here-if-data-centers-will-adopt
[4] https://towardsdatascience.com/chatgpts-electricity-consumption-7873483feac4

https://doi.org/10.1016/j.neucom.2024.128096
Received 22 December 2023; Received in revised form 31 May 2024; Accepted 15 June 2024
Available online 22 June 2024

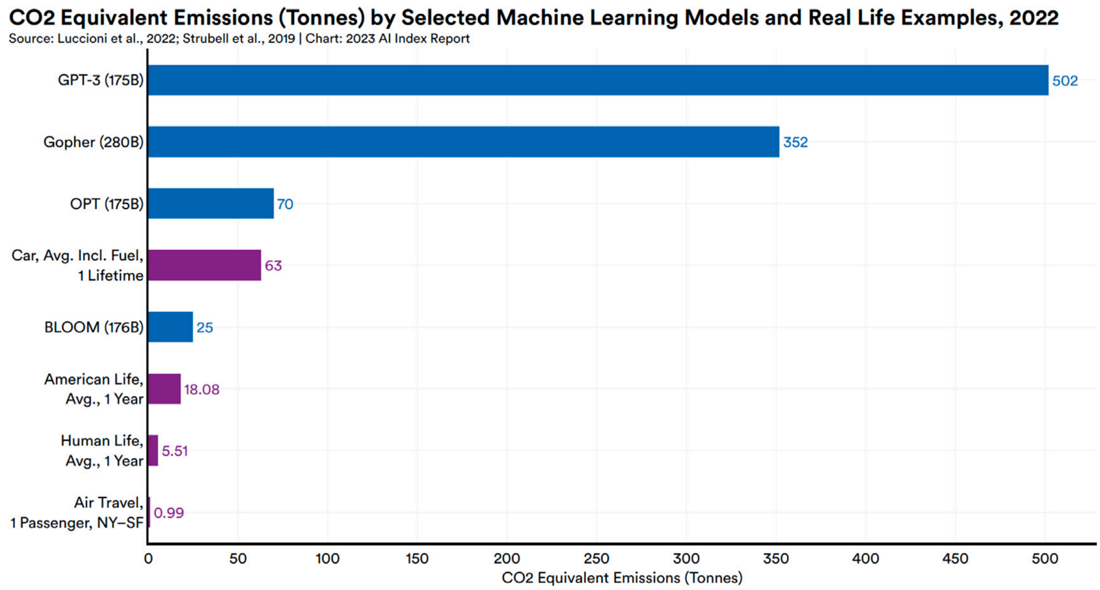

Fig. 1. CO2 equivalent emissions for training ML models (blue) and of real-life cases (violet). In brackets, the billions of parameters adjusted for each model.

Traditional ML algorithms typically require large amounts of data and computational power, resulting in significant energy consumption by the algorithms, water consumption to refrigerate data centers holding training data, and increased greenhouse gas (GHG) emissions. Green AI seeks to mitigate its environmental impacts by optimizing algorithms, improving hardware efficiency, and adopting sustainable data management practices. Green AI, offering energy-effective solutions through cloud centers and mobile/edge devices, is characterized by a low carbon footprint, better quality data, small models, low computational complexity, and logical transparency. To ensure people's trust, it also offers clear and logical decision-making processes, thus adding social sustainability as a further advantage.

AI is associated with an increasing economic cost, which means that most key ML developments are in the hands of large companies with the necessary vast resources, economic, human, and computational. Fig. 2[5] shows the economic costs of training modern ML models, e.g., GPT-2 trained with 1.5 billion of parameters in 2019 cost an estimated 50,000 USD, while PaLM trained with 540 billion parameters in 2022 cost 8 million USD; thus, PaLM was 360 times bigger and 160 times more expensive.

According to the existing literature [2], green algorithms are usually defined as algorithms "capable of maximizing the energy efficiency and reducing the environmental impact of AI models, while supporting the use of this technology to respond to different environmental challenges". Thus, two types of algorithms are referred to: algorithms that are green by design, i.e., energy efficient in both training and use, and algorithms specifically trained and used to tackle environmental challenges (as described, e.g., in the Paris Agreement on climate change, the UN's Sustainable Development Goals (SDGs)[6], and the more recent European Green Deal[7]). These systems are often referred as green-*in* AI and green-*by* AI, respectively.

We explore the emerging field of green AI and green algorithms in terms of the various approaches, methodologies, and innovations that aim to make AI and ML more environmentally sustainable (Fig. 3). We also review the key challenges and opportunities posed by reducing energy consumption, minimizing carbon emissions, and promoting ethical and responsible AI practices. Adoption of those approaches not only has environmental advantages – key for the future and mandatory in the EU [3] (at least for high-risk systems) – but also leads to cost savings and increased efficiency without compromising performance or accuracy.

The remainder of this paper is structured as follows: in Section 2, we explore the different ways AI makes significant contributions to combating climate change and supporting the Green Deal (green-by AI); Section 3 explores various strategies aimed at minimizing the resource consumption associated with AI models (green-in AI); Section 4 briefly outlines the environmental impact of ML algorithms, along with relevant tools and frameworks; Section 5 outlines best practices and regulatory concepts that foster environmentally conscious AI and finally, Section 5 investigates emerging trends in the realm of green AI.

2. Green-by AI

AI undoubtedly holds significant promise in terms of contributing to the realization of the Green Deal and concurrently diminishing its own environmental impact. AI can play a pivotal role in reducing GHG emissions and enhancing efficiency across sectors encompassing energy production and consumption, agriculture, land use, biodiversity management, communications, transportation, and smart mobility, etc. Moreover, AI's growing utility extends to effectively addressing and adapting to climate change by furnishing robust prediction, resilience, and strategic management tools.

Vinuesa et al. [4], for instance, in an analysis of the impact of AI in accomplishing the UN's SDGs, found that AI could be an enabler in 134 targets, although it could also be an inhibitor in 59 targets. The main areas and applications where AI can extensively be used to improve sustainability are described below.

2.1. Energy efficiency

Reducing energy consumption is a key challenge for a more sustainable society. AI, particularly through smart grids, can potentially reduce overall electricity needs by optimizing alignment between regional power generation and local demand. Unlike traditional grids, which facilitate one-way electricity flow from generators to consumers, smart grids allow for variable magnitude and direction of electricity flows. This constant balancing of supply and demand enhances overall efficiency.

[5] https://aiindex.stanford.edu/report/
[6] https://sdgs.un.org/goals
[7] https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

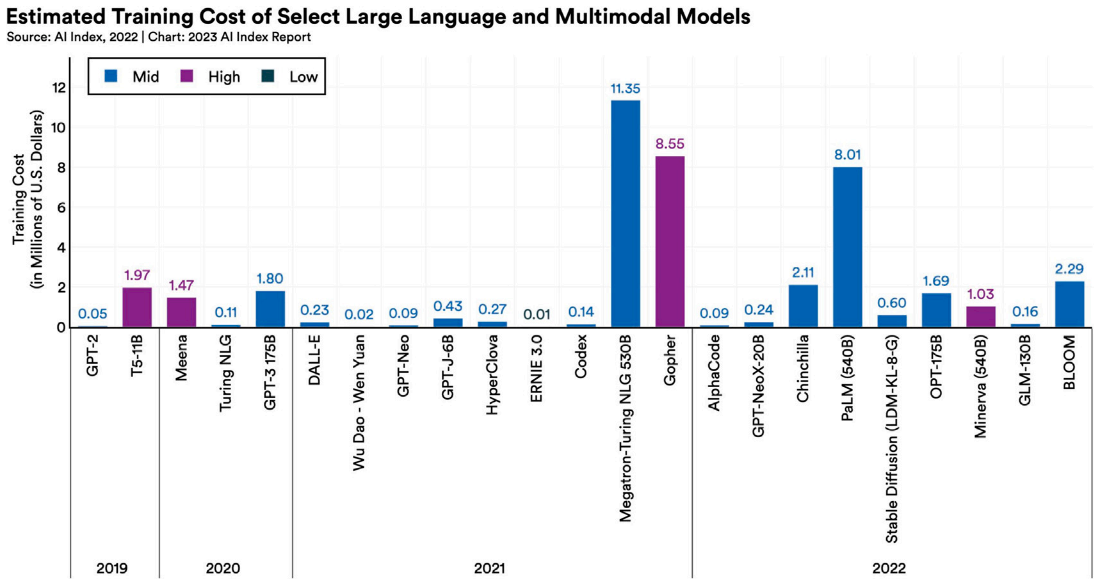

Fig. 2. Estimated training costs of large language and multimodal models. The colors indicate if estimates are high, mid-level, or low.

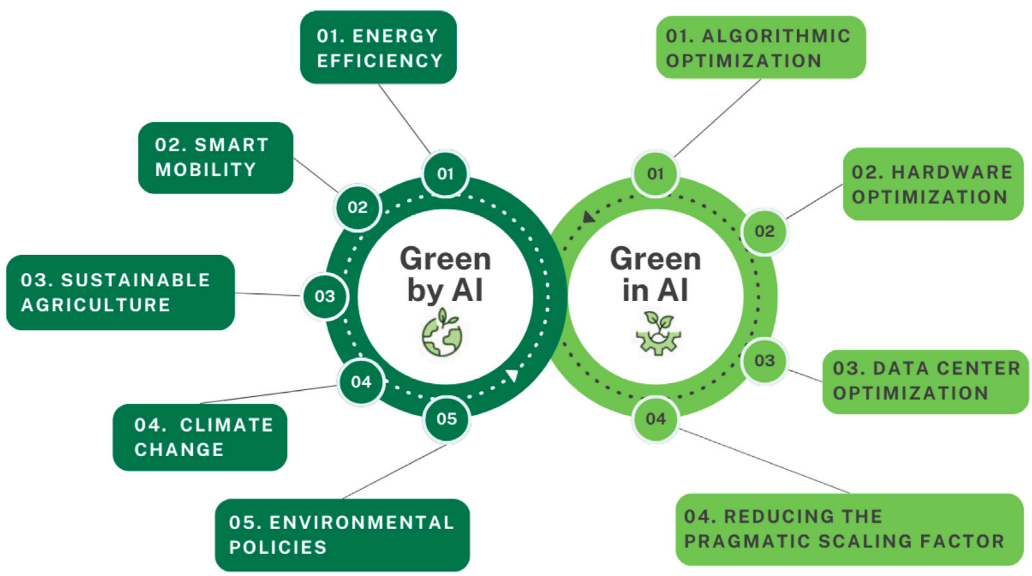

Fig. 3. Overview of green-in vs green-by algorithms.

ML techniques can be applied to predict renewable energy production, essential for seamless integration into a grid. The variability of renewable energy sources poses a challenge to reliable energy generation, prompting research into renewable energy forecasting. Accurate forecasting of solar and wind power is crucial to enhancing service quality and optimizing power management [5]. Deep neural networks (NNs) are among the most widely used approach to wind energy forecasting [6–8], whereas hybrid methods are typically used for solar energy forecasting, often combining deep NNs, recurrent NNs, and long short-term memory networks [9–11]. In these models, where real-time data are leveraged and both historical data and outputs from physical models are analyzed, successful development relies heavily on AI-enabled tools, given smart grid intricacies, uncertainties in their development, and the substantial volumes of real-time data collected.

Green AI can also contribute to making structures more energy efficient. ML models can analyze sensor data from smart buildings [12,13] and cities [14,15] to optimize heating, ventilation, and air conditioning (HVAC) systems, lighting, and energy usage patterns, thereby resulting in significant energy savings and reduced carbon emissions [16,17].

2.2. Smart mobility

AI plays a crucial role in advancing smart mobility and transforming traditional transportation systems into efficient, responsive, sustainable networks. As urban populations continue to grow, challenges in large cities, such as traffic congestion and environmental pollution, are escalating. Smart cities can alleviate these problems, fostering economic growth while enhancing overall quality of life for residents [18].

Through real-time data analysis, AI can predict traffic patterns, optimize routes, and alleviate congestion. The traffic prediction literature includes research into feature-based models [19], Gaussian process models [20], state-space models [21], and deep learning models [22]. AI-powered smart mobility systems can also enhance public transportation through dynamic scheduling that ensures timely arrivals and departures.

AI also contributes to autonomous vehicle (AV) development, which improves safety and efficiency while reducing traffic accidents, e.g., AI can execute fundamental tasks such as road following and obstacle detection [23]. ML can contribute to advancing AV technologies by minimizing energy consumption; Wu et al. [24], for instance, employed reinforcement learning to design AV controllers that effectively manage traffic interactions.

Integration of AI in smart mobility also facilitates the implementation of shared transportation services and supports the creation of eco-friendly modes of transport, contributing to a more sustainable and interconnected urban environment.

2.3. Sustainable agriculture

AI applications in agriculture include precision farming, based on data from sensors, satellites, and drones analyzed by ML algorithms. Farmers are provided with valuable insights into crop health, soil conditions, and irrigation needs, enabling them to make precise and targeted use of water, fertilizers, and pesticides, and thereby reducing environmental impact and enhancing resource efficiency. AI-powered predictive analytics also aid in crop yield forecasting and disease detection, allowing farmers to implement timely interventions and minimize losses [25].

Examples of applications include convolutional NNs used to build models for crop yield prediction, based on NDVI and RGB data acquired from unmanned aerial vehicles (UAVs) [26]. Given that groundwater resources are pivotal for agriculture, Pham et al. [27] conducted a comparative analysis to assess the effectiveness of ML models, including random forest (RF) and support vector machines (SVMs), for predicting groundwater levels. Another application is texture classification, which plays a crucial role in agricultural contexts, particularly as UAVs are increasingly garnering attention for their applications in this domain. Employing an efficient and interpretable generalized matrix learning vector quantization (GMLVQ) approach, Shumska et al. [28] describe a framework for classifying multispectral images, demonstrating the performance of different model designs and comparing them to established benchmarks for soil dataset classification.

Additional research aimed at supporting the agricultural sector proposes implementation of advanced technologies such as an agricultural IoT remote assistance system [29]: real-time data from farm fields triggers alert messages for low water levels and pressures, using classifiers that combine k-nearest neighbor (kNN) with NNs. The system also makes recommendations based on vital measurement data from farm fields, using modified fuzzy clustering and an attractiveness-based particle swarm optimization (PSO) algorithm.

AI also contributes to labor efficiency and reduces the ecological footprint of traditional farming methods via smart farming equipment, such as autonomous tractors and robotic harvesters. Finally, quantum machine learning could be used for agricultural mechanization and plant disease detection [30].

2.4. Climate change

In the battle against climate change, AI makes substantial mitigation and adaptation contributions across various domains [31]. Since electricity systems contribute approximately 25% to annual human-induced GHG emissions [32], ML techniques have been used to address this issue, e.g., predicting supply and demand. Various forecasting methods have been used to predict short-to medium-term demand [33] and the availability of solar power [34] and wind power [35]. These approaches incorporate historical data, physical model outputs, images, and video data, using supervised ML techniques, fuzzy logic, and hybrid physical models for analysis. Here too, quantum computing could accelerate improvements in large-scale technologies, such as solar panels and batteries [36].

In the shift to low-carbon electricity, ML has applications in mitigating methane leaks in natural gas pipelines and compressor stations — a necessary interim solution to reducing emissions from fossil fuels during societal transition. A computer-vision methodology for automated leak detection has been described [37], based on convolutional NNs trained on methane leak images. ML can also contribute to emissions reduction by reducing reliance on carbon-intensive materials and transforming industrial processes to operate on low-carbon energy, and even redesigning the chemistry of structural materials, such as in a study [38] that integrates ML with generative design to create structural products requiring less raw material and reducing the use of cement and steel.

2.5. Environmental policies

AI integration in the design of environmental policies represents a transformative approach to enhancing sustainability across diverse sectors. AI's analytical capabilities, coupled with its capacity to process vast datasets, empower policymakers to formulate more effective strategies for environmental conservation and resource management. By leveraging ML algorithms, AI can discern patterns, identify trends, and predict potential outcomes, enabling the creation of policies that are not only responsive to current challenges but also anticipatory of future environmental needs [39,40]. Another technology that can be used in this area is agent-based modeling, which enables the design of targeted strategies to engage citizens in necessary change, based on taking collective and individual values into account to detect emergent behavior from interactions and small personal changes [41,42].

AI-driven policy design is a powerful tool in the pursuit of sustainable development, ranging from optimizing energy consumption to implementing eco-friendly practices in urban planning. The precision and adaptability inherent to AI systems hold the promise of ushering in a new era of policy innovation in which data-driven insights contribute to fostering a resilient and environmentally aware society.

3. Green-in AI

The integration of AI in efforts to enhance sustainability represents a promising frontier with diverse applications across multiple sectors. However, in the quest to enhance sustainability through AI, it is imperative that the AI systems themselves do not become a counterproductive force by demanding excessive amounts of energy. For AI to truly serve as a tool for achieving energy reductions, algorithms and computational processes must be designed with efficiency in mind. This means leveraging AI solutions that are not only effective in optimizing energy use in applications but are also inherently low energy consumers. Striking this balance is crucial to ensuring that the net impact of employing AI contributes positively to sustainability goals, rather than exacerbating the very issues it aims to solve. This debate revolves around the difference between red AI and green AI [43]. The concept of red AI, which "buys" better results at the cost of using massive computational resources, was based on an analysis of 60 papers presented at the most prestigious conferences [44] that showed that the vast majority of papers (between 75% and 90% depending on the conference) prioritized accuracy over efficiency. A 2018 study[8] reveals that the computational needs to train large ML models have doubled every 3.4 months since 2012 (deviating quite a bit from Moore's Law, which states that this should happen close to every two years [45]).

However, the energy consumption of ML algorithms should not be viewed as an impossible goal and should not be assumed as a regrettable but necessary cost of progress in this field. Green-in AI is AI research that produces novel results while ideally reducing computational cost — or at least without increasing this cost. The specialized literature describes several strategies to reduce this computational cost, not only from the software perspective, but also focusing on hardware solutions that can reduce AI impact. Below we describe the most promising approaches.

[8] https://openai.com/research/ai-and-compute

3.1. Algorithm optimization

Making algorithms more efficient has many benefits over and above the reduction in their environmental footprint. One of the most productive strategies in green algorithm development is the design of optimization techniques that reduce the computational resource requirement, thus minimizing energy consumption. Areas of research that are active in decreasing both the memory footprint and the computational complexity of training models include sparse training methods [46–48], quantization techniques and energy-aware pruning [49–52], and low-precision arithmetic operations [53–55].

Other research has proposed using more efficient techniques. García-Castillo et al. [56] developed a novel and efficient method for feature selection in domain adaptation, using mutual information maximization (MIM) as opposed to the commonly used evolutionary algorithms, while Lourenço et al. [57] described a scalable and sustainable methodology for condition-based maintenance of wheel out-of-roundness, using locality-sensitive hashing to analyze extensive time series datasets.

3.2. Hardware optimization

Choosing more computationally efficient hardware can also contribute to energy savings, as some graphic processing units (GPUs), compared to other GPUs, have substantially higher efficiency in terms of floating point operations per second (FLOPS) per watt of power usage. Other specialized hardware accelerators are tensor processing units (TPUs) [58], tailored specifically for ML tasks, and with the ability to customize ML models to be used in that specific hardware [59,60].

Another important issue is parallelization — an obvious way to reduce the training time of algorithms by distributing computation among several processing cores. Anthony et al. [61] showed that, for a given task, increasing the number of cores to 15 improves execution times and reduces GHG emissions. However, emission levels deteriorate when the reduction in execution time is smaller than the relative increase in the number of cores, with experiments by those authors demonstrating how marginal improvements in runtime lead to disproportionately large emissions.

Finally, edge computing is also a key strategy in this context, as the idea is to perform computation at the locations where the data is collected or used, thus avoiding the need to transmit the data to a data center or to the cloud, while adapting to the limited computational and energy resources of IoT devices [62–64].

3.3. Data center optimization

The carbon footprint of a data center is directly proportional to its efficiency and the carbon intensity of its location. The latter is perhaps the most important factor in terms of total carbon footprint, due to great variability between countries — from less than 20 gCO2e kWh^{-1} in Norway and Switzerland to over 800 gCO2e kWh^{-1} in Australia, South Africa, and some US states [2]. Fig. 4 shows GHG emissions by European Union (EU) countries over four decades.[9]

To optimize data center use, researchers have developed algorithms and frameworks that dynamically manage server loads [65,66], adjust cooling systems [67,68], and optimize resource allocation to reduce energy consumption in data centers [69].

3.4. Pragmatic scaling factor reductions

Limiting the number of times an algorithm is run, especially those that are computationally expensive, is undoubtedly the easiest way to reduce energy consumption. Another possible strategy is to limit the time spent on hyperparameter tuning, e.g., using less exhaustive searches [70–72].

[9] https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-14/#tab-googlechartid_chart_41

4. Energy consumption calculation tools

Beyond algorithmic advances, researchers have also been working on frameworks and tools to assess the environmental impact of ML systems. ML risks contributing significantly to climate change if it follows the energy consumption trend of large models. However, if researchers and developers are aware of the energy and carbon footprint of their ML models, they are more likely to take ameliorating measures.

Considerable effort has been invested in creating standardized methods for calculating the carbon emissions associated with training models, as documented in various studies [2,73–76], and resulting in several tools (described below) for calculating and predicting the carbon footprint of AI. However, different carbon estimation tools report significantly discrepant results, and also tend to underestimate emissions, as reported in a recent analysis [77] that evaluated the carbon footprint of natural language processing (NLP) methods, using existing tools for measuring energy use and carbon emissions. Key reasons for disagreement between the tools include differing methodologies, hardware assumptions, utilization rates, software overheads, and geographical electricity mixes. Therefore, it seems clear that the lack of a universally accepted method for calculating carbon emissions complicates the process of standardizing reports and making comparisons.

The most popular tools currently in use for estimating carbon footprint are as follows:

- **CarbonTracker.**[10] This environmental monitoring tool is designed to track and analyze GHG emissions, particularly carbon dioxide, at various sources and locations. It uses a combination of approaches, including atmospheric measurements and statistical modeling, to estimate and visualize real-time carbon emissions. This tool is a valuable resource for researchers, policymakers, and environmental organizations, as it can help them gain insights into the impact of deep learning models (famously computationally and energy intensive).
- **CodeCarbon.**[11] This specialized software assists developers and organizations in tracking and managing the carbon emissions generated by their software and codebase. Once integrated into the development pipeline, it monitors the energy consumption and environmental impact of software applications and provides actionable insights and recommendations regarding carbon footprint reduction.
- **Green algorithms.**[12] The primary goal of this project is to reduce the environmental impact of computational processes by optimizing resource utilization, minimizing power consumption, and promoting sustainability in computing systems. Particularly relevant in the context of power-hungry users, such as data centers, supercomputers, and high-performance computing environments, it can be easily integrated with computational processes as it requires a minimum amount of information and does not interfere with existing code.
- **PowerTop.**[13] This powerful and open-source utility for Linux-based systems monitors and analyzes power consumption and management in real-time. Developed by Intel, it identifies power-hungry processes, devices, and components in computer systems, making it a valuable tool for optimizing energy efficiency and extending battery life on laptops and reducing power usage in servers. Displaying detailed information on power usage, it enables users to make informed decisions to conserve energy, reduce carbon emissions, and improve the overall sustainability of their Linux-based systems by fine-tuning power-related settings and identifying areas for improvement.

[10] https://carbontracker.org
[11] https://codecarbon.io/
[12] http://www.green-algorithms.org
[13] https://github.com/fenrus75/powertop

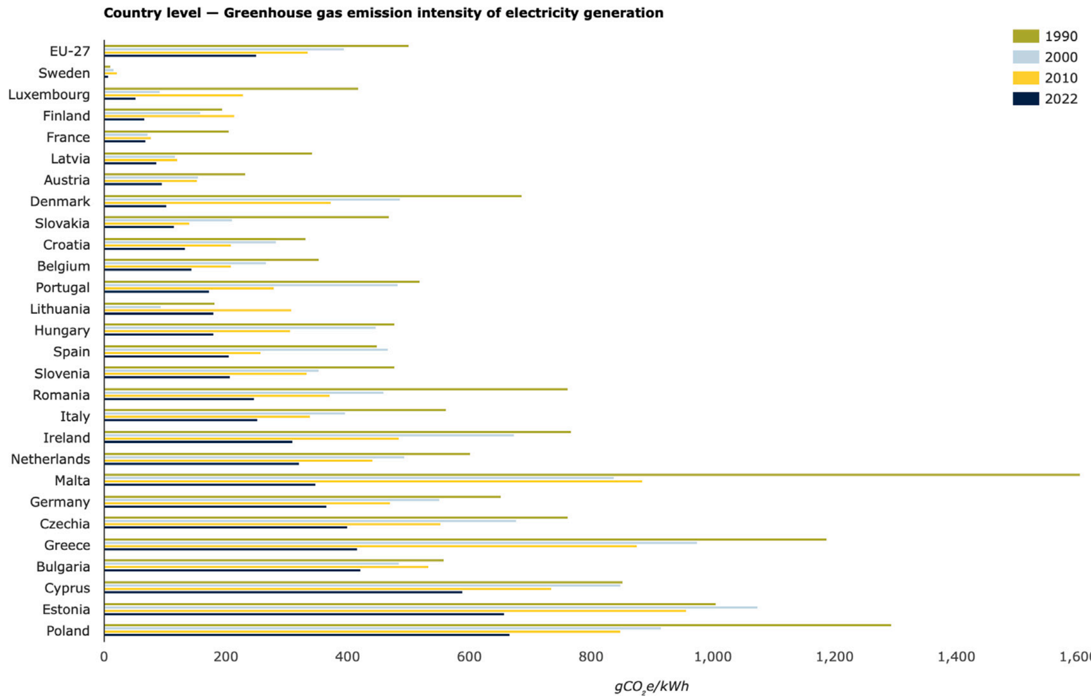

Fig. 4. Greenhouse gas emissions by different European Union countries.

5. Regulation and green AI

In view of the diverse tools available for calculating energy consumption in AI systems, it is evident that understanding and optimizing their carbon footprint is only the first step. The next critical phase involves the development and implementation of regulation and the promotion of green AI practices. This transition signifies a shift from merely measuring to actively managing and reducing the environmental impact of AI. By establishing guidelines and standards for energy efficiency in AI development, stakeholders can ensure that advances in AI not only drive innovation but also align with broader sustainability objectives. In fact, some companies have published best-practice guides on the matter. Google, for instance, has made four recommendations[14] that, it claims, can together reduce energy use by a factor of 100 and emissions by a factor of 1000:

- **Efficient ML model architectures.** Rather than use the biggest multi-purpose model available, efforts should be invested in developing reduced architectures that are capable of tackling the problem in hand, e.g., [78], model shrinking [79] and sparse [80] and compact architectures [81].
- **Processors and systems optimized for training ML models.** Dedicated deep learning hardware, such as TPUs, neuromorphic chips, and vision processing units (VPUs), offer significant energy advantages over conventional GPUs, as they improve performance and energy efficiency by 2x–5x [82]. TPUs, for instance, custom-designed to accelerate deep learning workloads at both the training and inference stages, are optimized for high throughput of low-precision arithmetic, which is common in NN computation. This specialization allows TPUs to execute deep learning tasks more efficiently than GPUs, translating to faster computation and lower energy consumption for the same tasks.
- **Cloud-based data centers.** Shifting computing operations from real-world premises to the cloud can significantly reduce energy consumption and emissions by 25% to 50% [83]. This efficiency gain is primarily due to the fact that cloud data centers are modern, purpose-built facilities optimized for energy-saving and capable of hosting massive numbers of servers with highly effective power usage effectiveness (PUE) ratios. In contrast, real-world data centers, which tend to be older and smaller, lack the scale to justify or implement the latest energy-efficient cooling and power distribution technologies.
- **Map optimization.** Major cloud service providers are increasingly investing in renewable energy sources to power their data centers, as, by leveraging wind, solar, and hydroelectric power, their carbon footprint is significantly reduced. Because individual businesses typically find it challenging to switch to renewable energy sources due to cost, availability, and logistical issues, a greener choice is the cloud, which offers the flexibility of selecting locations that maximize energy source use, potentially decreasing the overall carbon footprint by a factor of 5 to 10. Concerns may arise, however, that optimizing for the most eco-friendly locations could cause some sites to rapidly reach their capacity limits.

Although the involvement of researchers and companies is essential, it is imperative to go a step further and introduce regulations to govern AI that ensure responsible and sustainable advances in this rapidly evolving technological landscape.

Fostering responsible development and use of AI was mentioned as early as 2019 in the Ethics Guidelines for Trustworthy AI published by the High-Level Expert Group on AI in the EU [84]. The report states seven key requirements that AI systems should fulfill, including a requirement on societal and environmental wellbeing. The same group later released another report that contained an assessment list for trustworthy AI (ALTAI) [85], in which they also recommended supporting research initiatives that explore AI solutions that address global challenges, such as the SDGs,[15] whose progress could potentially be accelerated by AI. To critically examine resource use and algorithm energy consumption during training, the following questions are posed as a self-administered questionnaire for companies and researchers:

[14] https://blog.research.google/2022/02/good-news-about-carbon-footprint-of.html

[15] https://sdgs.un.org/goals

- Are there any potentially negative impacts of the AI system on the environment? If so, what are those potential impacts?
- Have mechanisms been established, wherever possible, to evaluate the environmental impact of the AI system, whether in terms of development, deployment, or use (e.g., energy used and carbon emissions)?
- Have measures been defined to reduce environmental impact over the lifecycle of the AI system?

According to the EU White Paper on AI published by the European Commission in 2020,[16] technology can be used to find solutions to climate change and environmental degradation (green-by AI), and can do so in an environmentally friendly manner (green-in AI) throughout the value chain, from data collection, storage, and processing to algorithm training and use. The AI Act,[17] an EU regulation agreed in negotiations with member states in December 2023 and approved on 13 March 2024, establishes obligations for AI systems based on their potential risks and impacts. This AI Act represents a strong compromise to fostering both the green-in and green-by perspectives described above. It particularly aims to safeguard fundamental rights, democracy, the rule of law, and environmental sustainability in high-risk AI, while also boosting innovation and positioning Europe as a leader in the field. Reporting energy efficiency is an additional obligation for high-impact general purpose AI models, particularly those posing systemic risk (namely, generative AI). For non-high-risk AI systems, encouraged is the development of codes of conduct that adhere to some or all of the mandatory requirements applicable to high-risk systems, adapted according to the system's intended purposes. Also encouraged is voluntary compliance with the requirements of the Ethics Guidelines for Trustworthy AI[18] and with environmental sustainability. The European AI Office and member states are responsible for promoting the development of codes of conduct for voluntary implementation of specific requirements, including minimizing the environmental impact of AI systems through energy-efficient programming and efficient design, training, and use. These codes of conduct should be based on clear objectives and key performance indicators to measure their effectiveness. Member states are also required to establish at least one national AI regulatory sandbox, i.e., a controlled environment to foster innovation and facilitate the development, training, testing, and validation of innovative AI systems for a limited time before entering the market. Personal data lawfully collected for other purposes may, interestingly, be processed in an AI regulatory sandbox, but solely for the purpose of developing, training, and testing certain AI systems meeting specific conditions in terms of a high level of protection and improvement of the environment, protection of biodiversity and against pollution, green transition measures, climate change mitigation and adaptation measures, energy sustainability, etc.

Regarding the USA, the recent (30 October 2023) Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence[19] only briefly mentions an objective to "promote the safe, responsible, and rights-affirming development and deployment of AI abroad to solve global challenges, such as advancing sustainable development and mitigating dangers to critical infrastructure". Apparently, therefore, the development of green algorithms will not be enforced by the US regulation. The situation in China is similar, as its regulation does not enforce sustainability restrictions on the development of AI.

[16] https://commission.europa.eu/system/files/2020-02/commission-white-paper-artificial-intelligence-feb2020_en.pdf

[17] https://www.europarl.europa.eu/doceo/document/TA-9-2024-0138_EN.pdf

[18] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[19] https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence/

Note that the information and communications technology (ICT) sector accounts for 3.9% of global GHG emissions[20] (surpassing global air travel), suggesting that the carbon footprint associated with AI, particularly in the case of large-scale generative models, is huge. Given this unsustainable burden for the planet and its inhabitants, we encourage the incorporation of sustainability as a regulatory requirement for the development of future AI algorithms [86] as required by the AI Act. As researchers and developers, we could at least start by using algorithm energy consumption measures in additions to accuracy and precision measures, as a means of raining awareness of a conscious use of resources in AI.

6. Future directions

As we step into the future, the need for convergence of AI with environmental sustainability is becoming increasingly apparent. This section explores a few emerging trends in green AI, highlighting how this innovative field is poised to shape a more sustainable and environmentally conscious future.

- **Explainable AI for environmental decision-making.** Explainable AI (XAI) is gaining prominence in green AI applications as a means of enhancing transparency and accountability. As AI systems are increasingly incorporated in environmental decision-making processes, the ability to understand and interpret the reasoning behind AI-generated recommendations becomes crucial. This is of special interest in green-by AI applications. XAI models could provide crucial information about the mechanisms that can lead to a more sustainable world. Early versions are already in use in fields like agriculture [87] and certain industrial sectors [88].
- **Eco-friendly AI hardware accelerators.** Innovation in hardware design is focusing on creating AI accelerators that are not only powerful but also eco-friendly [89]. This includes the development of processors that can execute AI algorithms with minimal energy consumption.
- **Neuromorphic computing**. This area, a paradigm shift in computing technology, draws inspiration from the human brain's architecture to develop more efficient and adaptive computing systems. The remarkably energy-efficient human brain is capable of performing complex tasks with much less energy than conventional computers. Neuromorphic computing emulates this efficiency by reducing the energy consumption of computational processes to levels akin to biological brains. It does this by leveraging spiking NNs (SNNs) to mimic biological NNs, resulting in substantial energy savings and performance improvements, particularly in AI applications requiring real-time processing and decision-making. A sustainability proposal by Oh et al. [90] to reduce the impact of technological waste is to create biodegradable NN hardware.
- **Energy-harvesting AI devices.** Research is underway to develop AI devices that can harvest energy from the surrounding environment to power AI systems [91], e.g., from ambient light, vibrations, and heat [92]. By integrating energy harvesting capabilities, AI devices could become more self-sufficient and so reduce the need for external power sources, contributing to a more sustainable deployment of AI.
- **AI for environmental conservation.** AI is playing a pivotal role in environmental conservation through innovative applications such as robotic pollinators in agriculture [93] and ocean AI [94]. AI-driven robotic pollinators, by mimicking natural pollination patterns [95], address the decline in natural pollinators of crops.

[20] https://dl.acm.org/doi/pdf/10.1145/3483410

This technology not only safeguards food security but also promotes sustainable farming practices. Ocean AI, which is based on the deployment of underwater drones equipped with advanced sensors to monitor and protect marine ecosystems [96], contributes to marine conservation efforts by tracking marine life, detecting pollution [97], and identifying illegal fishing activities [98]. Together, these advances showcase how AI is becoming indispensable to safeguarding biodiversity, promoting sustainable practices, and mitigating environmental threats in both terrestrial and aquatic ecosystems.

While we have explored several exciting fields and future trends in green AI, it is important to acknowledge that the landscape is dynamic and continually evolving. The applications discussed above represent just a glimpse into the vast potential of green AI, and there is a high likelihood that more innovative uses will emerge in the very near future. As technology advances, researchers, engineers, and environmentalists are likely to discover novel ways to integrate AI into diverse realms of sustainability, addressing challenges and creating new opportunities. The convergence of AI and environmental awareness is a fertile ground for exploration, and ongoing research and developments in this field are poised to unveil a multitude of applications that could significantly contribute to a more sustainable and eco-friendly future.

CRediT authorship contribution statement

Verónica Bolón-Canedo: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Laura Morán-Fernández:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Brais Cancela:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Amparo Alonso-Betanzos:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Veronica Bolon-Canedo reports financial support was provided by Spain Ministry of Science and Innovation. Amparo Alonso-Betanzos reports financial support was provided by Spain Ministry of Science and Innovation. Brais Cancela reports financial support was provided by Spain Ministry of Science and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported by CITIC, a Research Center accredited by Galician University System, which is funded by "Consellería de Cultura, Educación e Universidade from Xunta de Galicia", supported in an 80% through ERDF Funds, ERDF Operational Programme Galicia 2014–2020, and the remaining 20% by "Secretaría Xeral de Universidades" (Grant ED431G 2019/01). It was also partially funded by Xunta de Galicia/FEDER-UE under Grant ED431C 2022/44; Ministerio de Ciencia e Innovación MCIN/AEI/10.13039/501100011033 and "NextGenerationEU"/PRTR under Grants [PID2019-109238GB-C22; PID2021-128045OA-I00; TED2021-130599A-I00] and Ministry for Digital Transformation and Civil Service under grant TSI-100925-2023-1. Funding for open access charge: Universidade da Coruña/CISUG

References

[1] D. Patterson, J. Gonzalez, Q. Le, C. Liang, L.-M. Munguia, D. Rothchild, D. So, M. Texier, J. Dean, Carbon emissions and large neural network training, 2021, arXiv:2104.10350.

[2] L. Lannelongue, J. Grealey, M. Inouye, Green algorithms: quantifying the carbon footprint of computation, Adv. Sci. 8 (12) (2021) 2100707.

[3] European Union, Artificial intelligence act European parliament legislative resolution of 13 march 2024 on the proposal for a regulation of the European parliament and of the council on laying down harmonised rules on artificial intelligence (artificial intelligence act) and amending certain union legislative acts (com(2021)0206 – C9-0146/2021 – 2021/0106(COD)), 2024, URL https://www.europarl.europa.eu/doceo/document/TA-9-2024-0138_EN.pdf.

[4] R. Vinuesa, H. Azizpour, I. Leite, M. Balaam, V. Dignum, S. Domisch, A. Felländer, S.D. Langhans, M. Tegmark, F. Fuso Nerini, The role of artificial intelligence in achieving the sustainable development goals, Nature Commun. 11 (1) (2020) 1–10.

[5] S. Aslam, H. Herodotou, S.M. Mohsin, N. Javaid, N. Ashraf, S. Aslam, A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids, Renew. Sustain. Energy Rev. 144 (2021) 110992.

[6] H.-z. Wang, G.-q. Li, G.-b. Wang, J.-c. Peng, H. Jiang, Y.-t. Liu, Deep learning based ensemble approach for probabilistic wind power forecasting, Appl. Energy 188 (2017) 56–70.

[7] J. Chen, G.-Q. Zeng, W. Zhou, W. Du, K.-D. Lu, Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization, Energy Convers. Manage. 165 (2018) 681–695.

[8] K.-P. Lin, P.-F. Pai, Y.-J. Ting, Deep belief networks with genetic algorithms in forecasting wind speed, IEEE Access 7 (2019) 99244–99253.

[9] D. Díaz-Vico, A. Torres-Barrán, A. Omari, J.R. Dorronsoro, Deep neural networks for wind and solar energy prediction, Neural Process. Lett. 46 (2017) 829–844.

[10] M.C. Sorkun, C. Paoli, Ö.D. Incel, Time series forecasting on solar irradiation using deep learning, in: 2017 10th International Conference on Electrical and Electronics Engineering, (ELECO), IEEE, 2017, pp. 151–155.

[11] M. Abdel-Nasser, K. Mahmoud, Accurate photovoltaic power forecasting models using deep LSTM-RNN, Neural Comput. Appl. 31 (2019) 2727–2740.

[12] B. Qolomany, A. Al-Fuqaha, A. Gupta, D. Benhaddou, S. Alwajidi, J. Qadir, A.C. Fong, Leveraging machine learning and big data for smart buildings: A comprehensive survey, IEEE Access 7 (2019) 90316–90356.

[13] A.-D. Pham, N.-T. Ngo, T.T.H. Truong, N.-T. Huynh, N.-S. Truong, Predicting energy consumption in multiple buildings using machine learning for improving energy efficiency and sustainability, J. Clean. Prod. 260 (2020) 121082.

[14] M. Zekić-Sušac, S. Mitrović, A. Has, Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities, Int. J. Inf. Manage. 58 (2021) 102074.

[15] T.M. Ghazal, M.K. Hasan, M. Ahmad, H.M. Alzoubi, M. Alshurideh, Machine learning approaches for sustainable cities using internet of things, in: The Effect of Information Technology on Business and Marketing Intelligence Systems, Springer, 2023, pp. 1969–1986.

[16] N. Milojevic-Dupont, F. Creutzig, Machine learning for geographically differentiated climate change mitigation in urban areas, Sustainable Cities Soc. 64 (2021) 102526.

[17] M. Zhang, A.-A. Kafy, P. Xiao, S. Han, S. Zou, M. Saha, C. Zhang, S. Tan, Impact of urban expansion on land surface temperature and carbon emissions using machine learning algorithms in wuhan, China, Urban Clim. 47 (2023) 101347.

[18] Z.-G. Chen, Z.-H. Zhan, S. Kwong, J. Zhang, Evolutionary computation for intelligent transportation in smart cities: A survey, IEEE Comput. Intell. Mag. 17 (2) (2022) 83–102.

[19] W. Li, J. Cao, J. Guan, S. Zhou, G. Liang, W.K. So, M. Szczecinski, A general framework for unmet demand prediction in on-demand transport services, IEEE Trans. Intell. Transp. Syst. 20 (8) (2018) 2820–2830.

[20] D. Salinas, M. Bohlke-Schneider, L. Callot, R. Medico, J. Gasthaus, High-dimensional multivariate forecasting with low-rank gaussian copula processes, Adv. Neural Inf. Process. Syst. 32 (2019).

[21] P. Duan, G. Mao, W. Liang, D. Zhang, A unified spatio-temporal model for short-term traffic flow prediction, IEEE Trans. Intell. Transp. Syst. 20 (9) (2018) 3212–3223.

[22] X. Yin, G. Wu, J. Wei, Y. Shen, H. Qi, B. Yin, Deep learning on traffic prediction: Methods, analysis, and future directions, IEEE Trans. Intell. Transp. Syst. 23 (6) (2021) 4927–4943.

[23] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L.D. Jackel, M. Monfort, U. Muller, J. Zhang, et al., End to end learning for self-driving cars, 2016, arXiv preprint arXiv:1604.07316.

[24] C. Wu, A. Kreidieh, E. Vinitsky, A.M. Bayen, Emergent behaviors in mixed-autonomy traffic, in: Conference on Robot Learning, PMLR, 2017, pp. 398–407.

[25] R. Sharma, S.S. Kamble, A. Gunasekaran, V. Kumar, A. Kumar, A systematic literature review on machine learning applications for sustainable agriculture supply chain performance, Comput. Oper. Res. 119 (2020) 104926.

[26] P. Nevavuori, N. Narra, T. Lipping, Crop yield prediction with deep convolutional neural networks, Comput. Electron. Agric. 163 (2019) 104859.

[27] Q.B. Pham, M. Kumar, F. Di Nunno, A. Elbeltagi, F. Granata, A.R.M.T. Islam, S. Talukdar, X.C. Nguyen, A.N. Ahmed, D.T. Anh, Groundwater level prediction using machine learning algorithms in a drought-prone area, Neural Comput. Appl. 34 (13) (2022) 10751–10773.
[28] M. Shumska, K. Bunte, Multispectral texture classification in agriculture, in: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2023.
[29] R. Veerachamy, R. Ramar, Agricultural irrigation recommendation and alert (AIRA) system using optimization and machine learning in hadoop for sustainable agriculture, Environ. Sci. Pollut. Res. 29 (14) (2022) 19955–19974.
[30] M. Genemo, Quantum convolutional neural network for agricultural mechanization and plant disease detection, in: International Conference on Image Processing and Capsule Networks, Springer, 2023, pp. 225–237.
[31] D. Rolnick, P.L. Donti, L.H. Kaack, K. Kochanski, A. Lacoste, K. Sankaran, A.S. Ross, N. Milojevic-Dupont, N. Jaques, A. Waldman-Brown, et al., Tackling climate change with machine learning, ACM Comput. Surv. 55 (2) (2022) 1–96.
[32] Change, IPCC Climate, et al., Mitigation of climate change, Contrib. Working Group III Fifth Assess. Rep. Intergov. Panel Clim. Change 1454 (2014) 147.
[33] T. Hong, S. Fan, Probabilistic electric load forecasting: A tutorial review, Int. J. Forecast. 32 (3) (2016) 914–938.
[34] R. Ahmed, V. Sreeram, Y. Mishra, M. Arif, A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization, Renew. Sustain. Energy Rev. 124 (2020) 109792.
[35] G. Giebel, G. Kariniotakis, Wind power forecasting – a review of the state of the art, Renew. Energy Forecast. (2017) 59–109.
[36] I.H. Kim, Y.-H. Liu, S. Pallister, W. Pol, S. Roberts, E. Lee, Fault-tolerant resource estimate for quantum chemical simulations: Case study on li-ion battery electrolyte molecules, Phys. Rev. Res. 4 (2) (2022) 023019.
[37] J. Wang, L.P. Tchapmi, A.P. Ravikumar, M. McGuire, C.S. Bell, D. Zimmerle, S. Savarese, A.R. Brandt, Machine vision for natural gas methane emissions detection using an infrared camera, Appl. Energy 257 (2020) 113998.
[38] R.H. Kazi, T. Grossman, H. Cheong, A. Hashemi, G.W. Fitzmaurice, DreamSketch: Early stage 3D design explorations with sketching and generative design., in: UIST, vol. 14, 2017, pp. 401–414.
[39] N. Sánchez-Maroño, A. Rodríguez Arias, I. Lema-Lago, B. Guijarro-Berdiñas, A. Dumitru, A. Alonso-Betanzos, How agent-based modeling can help to foster sustainability projects, in: 26th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems, KES, 2022.
[40] R. García-Mira, A. Dumitru, A. Alonso-Betanzos, N. Sánchez-Maroño, O. Fontenla-Romero, T. Craig, J. Polhil, Testing scenarios to achieve workplace sustainability goals using backcasting and agent-based modeling, Environ. Behav. 49 (9) (2017) 1007–1027.
[41] N. Sánchez-Maroño, A. Alonso-Betanzos, O. Fontenla-Romero, C. Brinquis-Núñez, J.G. Polhill, T. Craig, A. Dumitru, R. García-Mira, An agent-based model for simulating environmental behavior in an educational organization, Neural Process. Lett. 42 (2015) 89–118.
[42] W. Jager, B. Guijarro-Berdiñas, L. Bouman, P. Antosz, A. Alonso Betanzos, D. Salt, J.G. Polhill, A. Rodríguez Arias, N. Sánchez-Maroño, Simulating the role of norms in processes of social innovation: Three case studies, J. Artif. Soc. Soc. Simul. (ISSN: 1460-7425) 27 (1) (2024) 6, http://dx.doi.org/10.18564/jasss.5168, URL http://jasss.soc.surrey.ac.uk/27/1/6.html.
[43] P. Dhar, The carbon impact of artificial intelligence., Nat. Mach. Intell. 2 (8) (2020) 423–425.
[44] R. Schwartz, J. Dodge, N.A. Smith, O. Etzioni, Green ai, Commun. ACM 63 (12) (2020) 54–63.
[45] G.E. Moore, Cramming more components onto integrated circuits, Proc. IEEE 86 (1) (1998) 82–85.
[46] C. Renggli, S. Ashkboos, M. Aghagolzadeh, D. Alistarh, T. Hoefler, SparCML: High-performance sparse communication for machine learning, in: Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis, 2019, pp. 1–15.
[47] Y. Tay, D. Bahri, L. Yang, D. Metzler, D.-C. Juan, Sparse sinkhorn attention, in: International Conference on Machine Learning, PMLR, 2020, pp. 9438–9447.
[48] S. Bibikar, H. Vikalo, Z. Wang, X. Chen, Federated dynamic sparse training: Computing less, communicating less, yet learning better, in: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 36, (6) 2022, pp. 6080–6088.
[49] A. Elgabli, J. Park, A.S. Bedi, C.B. Issaid, M. Bennis, V. Aggarwal, Q-GADMM: Quantized group ADMM for communication efficient decentralized machine learning, IEEE Trans. Commun. 69 (1) (2020) 164–181.
[50] S. Khirirat, S. Magnússon, A. Aytekin, M. Johansson, A flexible framework for communication-efficient machine learning, in: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, (9) 2021, pp. 8101–8109.
[51] G. Xiao, J. Lin, M. Seznec, H. Wu, J. Demouth, S. Han, Smoothquant: Accurate and efficient post-training quantization for large language models, in: International Conference on Machine Learning, PMLR, 2023, pp. 38087–38099.
[52] T.-J. Yang, Y.-H. Chen, V. Sze, Designing energy-efficient convolutional neural networks using energy-aware pruning, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 5687–5695.
[53] O. Zafrir, G. Boudoukh, P. Izsak, M. Wasserblat, Q8bert: Quantized 8bit bert, in: 2019 Fifth Workshop on Energy Efficient Machine Learning and Cognitive Computing-NeurIPS Edition, (EMC2-NIPS), IEEE, 2019, pp. 36–39.
[54] Z. Liu, Y. Wang, K. Han, W. Zhang, S. Ma, W. Gao, Post-training quantization for vision transformer, Adv. Neural Inf. Process. Syst. 34 (2021) 28092–28103.
[55] S. Suárez-Marcote, L. Morán-Fernández, V. Bolón-Canedo, Logarithmic division for green feature selection: an information-theoretic approach, in: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2023.
[56] G. Castillo-García, L. Morán-Fernández, V. Bolón-Canedo, Efficient feature selection for domain adaptation using mutual information maximization, in: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2023.
[57] A. Lourenço, C. Ferraz, J. Meira, G. Marreiros, V. Bolón-Canedo, A. Alonso-Betanzos, Automated green machine learning for condition-based maintenance, in: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2023.
[58] N. Jouppi, G. Kurian, S. Li, P. Ma, R. Nagarajan, L. Nai, N. Patil, S. Subramanian, A. Swing, B. Towles, et al., Tpu v4: An optically reconfigurable supercomputer for machine learning with hardware support for embeddings, in: Proceedings of the 50th Annual International Symposium on Computer Architecture, 2023, pp. 1–14.
[59] M. Osta, M. Alameh, H. Younes, A. Ibrahim, M. Valle, Energy efficient implementation of machine learning algorithms on hardware platforms, in: 2019 26th IEEE International Conference on Electronics, Circuits and Systems, (ICECS), IEEE, 2019, pp. 21–24.
[60] D. Stamoulis, R. Ding, D. Wang, D. Lymberopoulos, B. Priyantha, J. Liu, D. Marculescu, Single-path nas: Designing hardware-efficient convnets in less than 4 hours, in: Joint European Conference on Machine Learning and Knowledge Discovery in Databases, Springer, 2019, pp. 481–497.
[61] L.F.W. Anthony, B. Kanding, R. Selvan, Carbontracker: Tracking and predicting the carbon footprint of training deep learning models, 2020, arXiv preprint arXiv:2007.03051.
[62] S. Singh, R. Sulthana, T. Shewale, V. Chamola, A. Benslimane, B. Sikdar, Machine-learning-assisted security and privacy provisioning for edge computing: A survey, IEEE Internet Things J. 9 (1) (2021) 236–260.
[63] Y. Wan, Y. Qu, L. Gao, Y. Xiang, Privacy-preserving blockchain-enabled federated learning for B5G-driven edge computing, Comput. Netw. 204 (2022) 108671.
[64] D. Novoa-Paradela, O. Fontenla-Romero, B. Guijarro-Berdiñas, Fast deep autoencoder for federated learning, Pattern Recognit. 143 (2023) 109805, http://dx.doi.org/10.1016/j.patcog.2023.109805, URL https://www.sciencedirect.com/science/article/pii/S0031320323005034.
[65] A. Ghasemi, A. Toroghi Haghighat, A multi-objective load balancing algorithm for virtual machine placement in cloud data centers based on machine learning, Computing 102 (2020) 2049–2072.
[66] H. Dong, A. Munir, H. Tout, Y. Ganjali, Next-generation data center network enabled by machine learning: Review, challenges, and opportunities, IEEE Access 9 (2021) 136459–136475.
[67] Y. Li, Y. Wen, D. Tao, K. Guan, Transforming cooling optimization for green data center via deep reinforcement learning, IEEE Trans. Cybern. 50 (5) (2019) 2002–2013.
[68] Z. Cao, X. Zhou, H. Hu, Z. Wang, Y. Wen, Toward a systematic survey for carbon neutral data centers, IEEE Commun. Surv. Tutor. 24 (2) (2022) 895–936.
[69] R. Moreno-Vozmediano, R.S. Montero, E. Huedo, I.M. Llorente, Efficient resource provisioning for elastic cloud services based on machine learning techniques, J. Cloud Comput. 8 (1) (2019) 1–18.
[70] J. Bergstra, Y. Bengio, Random search for hyper-parameter optimization., J. Mach. Learn. Res. 13 (2) (2012).
[71] J. Snoek, H. Larochelle, R.P. Adams, Practical bayesian optimization of machine learning algorithms, Adv. Neural Inf. Process. Syst. 25 (2012).
[72] L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh, A. Talwalkar, Hyperband: A novel bandit-based approach to hyperparameter optimization, J. Mach. Learn. Res. 18 (1) (2017) 6765–6816.
[73] P. Henderson, J. Hu, J. Romoff, E. Brunskill, D. Jurafsky, J. Pineau, Towards the systematic reporting of the energy and carbon footprints of machine learning, J. Mach. Learn. Res. 21 (248) (2020) 1–43.
[74] K. Lottick, S. Susai, S.A. Friedler, J.P. Wilson, Energy usage reports: Environmental awareness as part of algorithmic accountability, 2019, arXiv preprint arXiv:1911.08354.
[75] T. Trébaol, CUMULATOR—a tool to quantify and report the carbon footprint of machine learning computations and communication in academia and healthcare, 2020.
[76] A.S. Luccioni, A. Hernandez-Garcia, Counting carbon: A survey of factors influencing the emissions of machine learning, 2023, arXiv preprint arXiv:2302.08476.
[77] N. Bannour, S. Ghannay, A. Névéol, A.-L. Ligozat, Evaluating the carbon footprint of NLP methods: a survey and analysis of existing tools, in: Proceedings of the Second Workshop on Simple and Efficient Natural Language Processing, 2021, pp. 11–21.
[78] G. Menghani, Efficient deep learning: A survey on making deep learning models smaller, faster, and better, ACM Comput. Surv. 55 (12) (2023) 1–37.
[79] J. Gou, B. Yu, S.J. Maybank, D. Tao, Knowledge distillation: A survey, Int. J. Comput. Vis. 129 (6) (2021) 1789–1819.

[80] T. Hoefler, D. Alistarh, T. Ben-Nun, N. Dryden, A. Peste, Sparsity in deep learning: Pruning and growth for efficient inference and training in neural networks, J. Mach. Learn. Res. 22 (241) (2021) 1–124.
[81] T. Zhao, Y. Xie, Y. Wang, J. Cheng, X. Guo, B. Hu, Y. Chen, A survey of deep learning on mobile devices: Applications, optimizations, challenges, and research opportunities, Proc. IEEE 110 (3) (2022) 334–354.
[82] S. Mittal, S. Vaishay, A survey of techniques for optimizing deep learning on GPUs, J. Syst. Archit. 99 (2019) 101635.
[83] M. Hodak, M. Gorkovenko, A. Dholakia, Towards power efficiency in deep learning on data center hardware, in: 2019 IEEE International Conference on Big Data (Big Data), IEEE, 2019, pp. 1814–1820.
[84] High-Level Expert Group on Artificial Intelligence, Ethics guidelines for trustworthy AI, 2018.
[85] High-Level Expert Group on Artificial Intelligence, Assessment list for trustworthy artificial intelligence (ALTAI) for self-assessment, 2020.
[86] P. Hacker, Sustainable AI regulation, 2023, arXiv:2306.00292.
[87] E. Delaney, D. Greene, L. Shalloo, M. Lynch, M.T. Keane, Forecasting for sustainable dairy produce: Enhanced long-term, milk-supply forecasting using k-nn for data augmentation, with prefactual explanations for xai, in: International Conference on Case-Based Reasoning, Springer, 2022, pp. 365–379.
[88] C. Turner, O. Okorie, J. Oyekan, XAI sustainable human in the loop maintenance, IFAC-PapersOnLine 55 (19) (2022) 67–72.
[89] H. Rahmani, D. Shetty, M. Wagih, Y. Ghasempour, V. Palazzi, N.B. Carvalho, R. Correia, A. Costanzo, D. Vital, F. Alimenti, et al., Next-generation IoT devices: Sustainable eco-friendly manufacturing, energy harvesting, and wireless connectivity, IEEE J. Microw. 3 (1) (2023) 237–255.
[90] S. Oh, H. Kim, S.E. Kim, M.-H. Kim, H.-L. Park, S.-H. Lee, Biodegradable and flexible polymer-based memristor possessing optimized synaptic plasticity for eco-friendly wearable neural networks with high energy efficiency, Adv. Intell. Syst. 5 (5) (2023) 2200272.
[91] S. Divya, S. Panda, S. Hajra, R. Jeyaraj, A. Paul, S.H. Park, H.J. Kim, T.H. Oh, Smart data processing for energy harvesting systems using artificial intelligence, Nano Energy (2022) 108084.
[92] A. Ali, H. Shaukat, S. Bibi, W.A. Altabey, M. Noori, S.A. Kouritem, Recent progress in energy harvesting systems for wearable technology, Energy Strategy Rev. 49 (2023) 101124.
[93] T. Hiraguri, T. Kimura, K. Endo, T. Ohya, T. Takanashi, H. Shimizu, Shape classification technology of pollinated tomato flowers for robotic implementation, Sci. Rep. 13 (1) (2023) 2159.
[94] K.N. Shivaprakash, N. Swami, S. Mysorekar, R. Arora, A. Gangadharan, K. Vohra, M. Jadeyegowda, J.M. Kiesecker, Potential for artificial intelligence (AI) and machine learning (ML) applications in biodiversity conservation, managing forests, and related services in India, Sustainability 14 (12) (2022) 7154.
[95] P. Joy, R. Thanka, B. Edwin, Smart self-pollination for future agricultural-a computational structure for micro air vehicles with man-made and artificial intelligence, Int. J. Intell. Syst. Appl. Eng. 10 (2) (2022) 170–174.
[96] A. Mandal, A.R. Ghosh, AI-driven surveillance of the health and disease status of ocean organisms: a review, Aquaculture Int. (2023) 1–12.
[97] N. Vardar, B. Bayram, A. Mishra, M. Palade, B. Şener, I. Boujmil, J. Scerri, A. Attard, İ. Demir, Autonomous network system with specialized and integrated multi-sensor technology for dynamic monitoring of marine pollution (SMARTPOL), J. ETA Marit. Sci. 11 (3) (2023).
[98] J. Angus, M. Bouvier-Brown, A. Robinson, Solar powered uncrewed surface vehicles (USVs) for Marine Protected Area (MPA) monitoring, in: OCEANS 2022, Hampton Roads, IEEE, 2022, pp. 1–5.

Verónica Bolón-Canedo received her B.S. (2009), M.S. (2010) and Ph.D. (2014) degrees in Computer Science from the Universidade da Coruña (Spain). After a postdoctoral fellowship in the University of Manchester, UK (2015), she is currently an Associate Professor in the Department of Computer Science and Information Technologies of the Universidade da Coruña. Her main current areas are machine learning and feature selection. She is co-author of more than 100 papers on these topics in international conferences and journals. She is member of the Young Academy of Spain and the Royal Academy of Sciences of Spain.

Laura Morán-Fernández received her B.S. (2015) and Ph.D. (2020) degrees in Computer Science from the University of A Coruña (Spain). She is currently an Assistant Professor in the Department of Computer Science and Information Technologies of the University of A Coruña. She received the Frances Allen Award (2021) from the Spanish Association of Artificial Intelligence. Her research interests include machine learning, feature selection and low precision. She has co-authored five book chapters, and more than 20 research papers in international journals and conferences.

Brais Cancela received the Ph.D. degree for his work in the area of computer vision in 2015 at the University of A Coruña (Spain). He is currently an Associate Professor in the Department of Computer Science, University of A Coruña (Spain). He has published more than 30 articles in journals and international conferences, and book chapters. His main current areas are convex optimization, machine learning and explainable models.

Amparo Alonso-Betanzos is a Full Professor in the area of Computer Science and Artificial Intelligence at CITIC-University of A Coru\˜a (UDC), Spain. Her research lines are the development of Scalable Machine Learning models, Reliable and Explainable Artificial Intelligence, and Frugal AI, among others. She has published more than 250 articles in journals and international conferences, and books and book chapters, participating in more than 60 competitive European, national and local research projects. She is a Senior Member of IEEE and ACM, and also a correspondent member of the Royal Academy of Sciences of Spain.