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Carbon Emission Quantification of Machine Learning: A Review

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***Abstract*—The rapid growth of machine learning (ML) technologies has raised significant concerns about their environmental impact, particularly regarding energy consumption and carbon emissions. This comprehensive review examines the intersection of ML and sustainability, synthesizing research from 2014 to 2024 to provide a holistic view of sustainable ML practices. This systematic review, encompassing over 200 peer-reviewed publications, reveals a growing emphasis on quantifying and mitigating the environmental footprint of ML systems. Key findings include: (1) a 300% increase in sustainable ML research since 2020; (2) the emergence of specialized carbon footprint quantification tools for ML; and (3) promising advancements in energy-efficient algorithms and green computing infrastructure. This research identifies critical challenges, including the lack of standardized sustainability metrics and the need for more robust life-cycle assessments of ML systems. The review also highlights the potential of transfer learning, federated learning, and hardware innovations in reducing ML's environmental impact. The analysis culminates in a novel framework for implementing sustainable practices in ML projects and a detailed roadmap for future research. This work provides researchers, practitioners, and policymakers with crucial insights to drive the development of more environmentally responsible ML technologies, ultimately contributing to global sustainability goals.**

***Index Terms*—Sustainability, Artificial Intelligence (AI), Machine Learning (ML), Carbon Emission, Sustainable Computing, ML Emission.**

I. Introduction

Sustainability in artificial intelligence (AI) refers to developing and deploying machine learning (ML) systems that balance technological advancement with environmental responsibility, social equity, and economic viability [1]. It involves minimizing energy consumption and carbon emissions, ensuring long-term relevance, optimizing resource use, and creating ethical, fair technologies that benefit society without compromising future generations' needs. ML plays a crucial role in innovating the sustainable energy technologies needed to combat climate change [2]–[5]. Green house gases (GHGs) trap heat in the lower atmosphere, warming the planet to a higher temperature than it would be without these gases. The main GHGs responsible for climate change are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (NOx). Carbon dioxide (CO_2) is the most important of these GHG contributions to global warming because of its higher concentration in the atmosphere. The current ML approach uncovered insights that can guide more targeted policies compared to traditional econometric analyses of CO_2 emissions drivers [6]. The ML approach uncovers insights that can guide more targeted policies compared to traditional econometric analyses of CO_2 emissions drivers. The findings provide a blueprint for Chinese policymakers to manage key driving factors in order to curb emissions by 2030 and to achieve carbon neutrality by 2060 while still enabling economic growth [7]. Though, AI can tackle climate impact [8], [9], the larger and deeper models in fields like natural language processing (NLP) are achieving near-perfect results on the shoulder of massive computations, leading to high energy consumption, which results in more carbon emissions [10]–[13]. Current Industry 5 frameworks [14] also promotes sustainability development.

A. Novelty and Gaps Addressed

This review paper offers several unique contributions to the field of sustainable ML:

1) Comprehensive Integration: While existing literature often focuses on isolated aspects of sustainability in ML, this review provides a holistic view by integrating perspectives from energy consumption, carbon emissions, algorithm efficiency, and environmental impact. This comprehensive approach addresses the gap in understanding the interconnected nature of sustainability challenges in ML.
2) Interdisciplinary Lens: Our review uniquely bridges the gap between computer science, environmental science, and sustainability studies. By synthesizing insights from these diverse fields, we provide a more nuanced understanding of the challenges and opportunities in sustainable ML.
3) Quantification Methods Analysis: This review offers the first comprehensive review and comparison of various carbon emission quantification methods specific to ML processes. This addresses a critical gap in standardizing sustainability metrics in the field.
4) Emerging Trends Identification: Through our systematic review, we identify and analyze emerging trends in sustainable ML that have not been collectively examined in previous reviews, such as the sustainability implications of federated learning and the intersection of ML security and emissions.
5) Practical Implementation Framework: We propose a novel framework for implementing sustainable practices in ML projects, addressing the gap between theoretical knowledge and practical application in the field.
6) Future Research Roadmap: Based on our analysis, we provide a detailed roadmap for future research directions

in sustainable ML, highlighting unexplored areas and potential breakthroughs.

By addressing these gaps, this review not only consolidates existing knowledge but also pushes the boundaries of sustainable ML research, providing researchers and practitioners with a comprehensive resource to drive future innovations in the field.

B. Contribution

The paper examines the most important sustainability aspects of ML models, including the core attack on ML, which may also affect sustainability. The primary emphasis of this review is:

1) Current state-of-the-art sustainability analysis.
2) Some theoretical and practical methods for quantifying carbon emissions.
3) The item focuses on the ML emission structure and its reduction technique.
4) Discuss some of the intersections between ML emissions and security.

C. Paper Organization

The remainder of the review has been organized as follows: In Section II, we discuss the methodology, followed by current carbon emission state-of-the-art methods in Sections III. Section IV reviews the potential for ML to be responsible for emissions. Then we analyze the different emission quantification methods in Section V, as well as the theoretical models in Section VI. Some intersections of ML security and emissions have been discussed in Section VII, and Section VIII illuminates some possible solutions for ML emission. While discussing some of our review's limitations in Section IX, our final section, Conclusion in Section X, concludes the paper. Overall, Figure 1 shows the organization of this review and Table I defines the list of all acronyms.

II. Methodology

We discuss two systematic review methodologies which are bibliometric [15] and PRISMA framework [16]. Bibliometric can help to evaluate the impact, structure, and development of scholarly literature by analyzing publication patterns, citation counts, authorship, and institutional or geographic collaboration to uncover research trends and influential contributors in a given field. While bibliometrics provides valuable insights, we acknowledge its limitations, such as the potential overemphasis on citation counts, which may not always correlate with research quality. Therefore, we use bibliometrics as a complementary tool alongside qualitative methods for a more nuanced understanding of research impact. On the other hand, we used PRISMA guidelines to enhance the clarity, reproducibility, and overall rigor of our systematic review. This approach also focuses on outlining essential items to be reported, including but not limited to research question, selection strategy, search criteria, data processing, and data extraction.

Fig. 1. The overall summary of the ML learning emission review.

To complement the bibliometric survey, we conducted an author-level and country-level collaboration analysis. A co-authorship network was constructed where nodes represent individual authors and edges denote shared publications. The graph's layout reflects the density and structure of research collaborations, with node size and color indicating the level of connectivity. Additionally, a geographic distribution analysis was performed by extracting country information from the affiliations in the bibliographic records. A choropleth map was generated to visualize the number of publications attributed to each country, providing a global overview of national contributions to sustainable ML research.

Figure 2 presents both the co-authorship network and the global distribution of publications, highlighting key collaboration patterns and research activity concentration across regions.

A. Systematic Review Process

Our review process, guided by the PRISMA framework to ensure a comprehensive and rigorous analysis of the literature on sustainable ML. The PRISMA process is defined in Figure 3 and consisted of the following steps:

1) Search Strategy: We conducted searches across multiple popular academic databases including Google Scholar, ACM Digital Library, IEEE Xplore, Springer, ScienceDirect, Txyz.ai. The search terms used are detailed in Table II and the number of literature retrieved during the search process are provided in Table III.
2) Inclusion Criteria:
   - Papers published between January 2014 and May 2024.

TABLE I
DEFINITIONS OF KEY ACRONYM IN THE STUDY.

Acronym	Full Form	Acronym	Full Form
ML	Machine Learning	**DICE**	Dynamic Integrated Model of Climate Economy
AI	Artificial Intelligence	**ACT**	Architectural Carbon Modeling Tool
GHGs	Green House Gases	**SCI**	Software Carbon Intensity
CO_2	Carbon Dioxide	**GPUs**	Graphical Processing Units
NLP	Natural Language Processing	**gCO_2eq/kWh**	Carbon Dioxide Equivalent per Kilowatt-Hour
CNC	Carbon Neutral Coefficient	**CEI**	Carbon Emissions Index
CO_2eq	Carbon Dioxide Equivalent	**SCAIS**	Sustainability Criteria and Indicators for AI Systems
kWh	Kilowatt-Hours	**ConvNet**	Convolutional Neural Networks
LCA	Life-Cycle Assessment	**LSA**	Layer Sustainability Analysis
RCPs	Representative Concentration Pathways	**DNN**	Deep Neural Networks
EIA	Environmental Impact Assessment	**RCTI**	Robustness Carbon Trade-off Index
FL	Federated Learning	**CRC**	Cost Per Unit of Robustness Change
DP	Differential Privacy	**TNs**	Tensor Networks
PII	Personally Identifiable Information	**AutoML**	Automated Machine Learning
LLMs	Large Language Models	**EVs**	Electric Vehicles
GenAI	Generative AI	**DT**	Digital Twin
EIT	Experiment Impact Tracker	**IoT**	Internet of Things
SCC	Social Cost of Carbon		

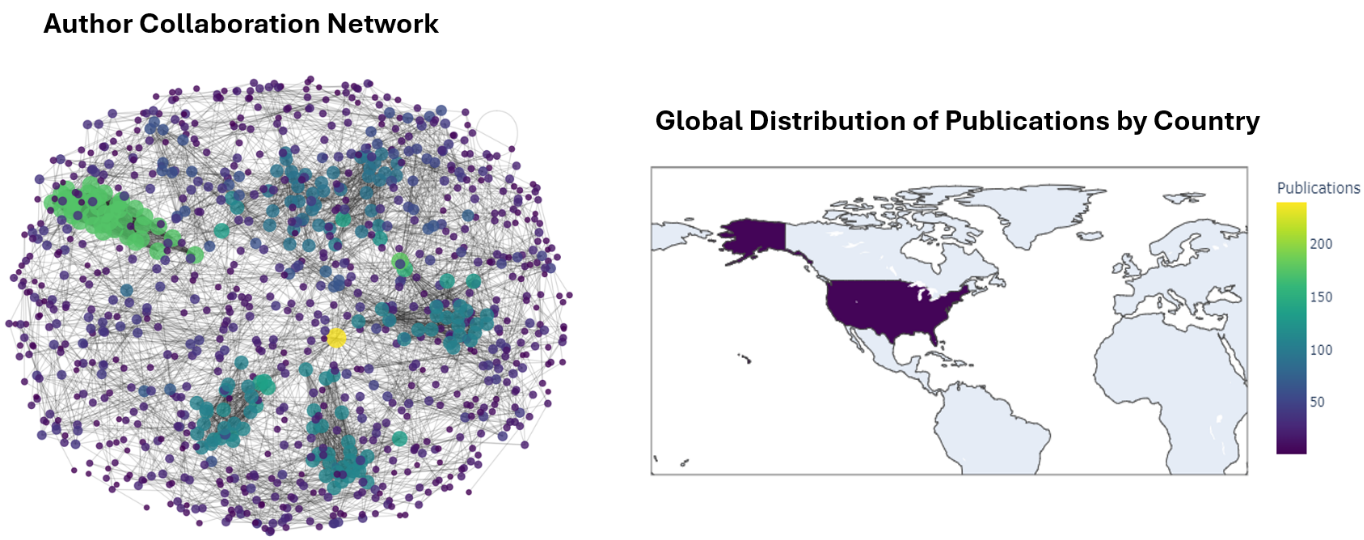

Fig. 2. Author collaboration network (left) and global distribution of publications by country (right). In the co-authorship graph, each node represents an author, and edges represent co-authored publications. The node color intensity and size indicate the degree of collaboration — with brighter and larger nodes (e.g., green and yellow) representing authors with higher connectivity in the network. The choropleth map visualizes the number of publications per country, highlighting the geographical distribution of contributions to sustainable ML literature.

- Peer-reviewed articles, conference proceedings, and book chapters.
- Studies focusing on sustainability aspects of ML, including energy efficiency, carbon emissions, and environmental impact.

3) Exclusion Criteria:
   - Non-peer-reviewed articles, preprints, and gray literature.
   - Studies not directly addressing sustainability in ML.
   - Papers focusing solely on general green computing without specific ML applications.
4) Screening Process: In this phase, we built few assessment criteria in order to assess the quality of our retrieved papers to include in our final screening process. The criteria are outlined in Table IV.
5) Data Extraction: We extracted key information from each included study, including research focus, methodologies used, main findings, and implications for sustainable ML.

B. Supplementary Sources

In addition to traditional academic databases, we leveraged cutting-edge AI-powered tools to enhance our literature search and analysis:

- OpenAI's ChatGPT[1]
- Google's Gemini[2]
- Microsoft's Copilot[3]

[1]https://chat.openai.com/
[2]https://gemini.google.com/
[3]https://copilot.microsoft.com/

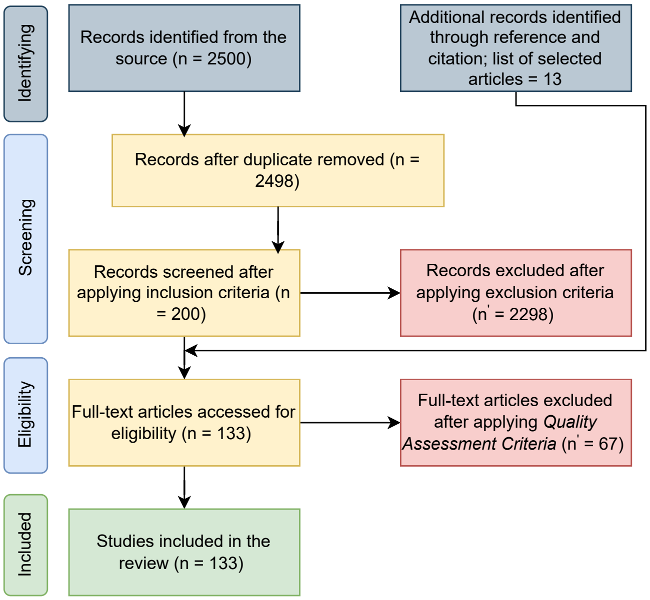

Fig. 3. The complete overview of the PRISMA selection process for this review.

- Anthropic's Claude[4]
- Txyz[5], an AI tool specifically designed for academic research and paper review.

These AI tools facilitated the identification of relevant research materials based on keywords such as sustainable ML, sustainable AI, ML carbon emissions, ML carbon quantification, and adversarial ML emission. By using the PRISMA framework, and advanced AI-powered tools, our methodology ensures a comprehensive and up-to-date review of the sustainable ML landscape. Using AI tools for our review papers helps us to summarize and organize large volumes of literature efficiently, saving time and enhancing writing clarity. Additionally, these tools support improving grammar and tone and suggesting relevant citations, supporting a faster drafting process. However, potential drawbacks include the risk of AI misinterpreting complex topics, generating inaccurate citations, or producing analysis that may be shallow or contextually inappropriate for the current context of the paper.

[4]https://claude.ai/
[5]https://app.txyz.ai/

TABLE II
LIST OF ML SUSTAINABILITY REVIEW SEARCH TERMS OR SEARCH KEYWORDS.

No.	Keywords Searched
1	ML survey, AI review, AI survey, ML Life-cycle Emission, ML literature review
2	Federated Learning emission, ML carbon, Adversarial Robustness Carbon Emission
3	ML sustainability data
4	ML emission and security
5	Sustainable computing
6	Green computing
7	ML Emission Quantification
8	Deep Leaning Emission
9	Green Metric

TABLE III
NO. OF PAPERS SUMMARIZED AND INCLUDED FROM EACH REPOSITORIES.

Paper Repositories	Total Count of Papers
Google Scholar	14,435
IEEE	93
Springer	1,210
ACM DL	2,359
ScienceDirect	666
Research Gate	39
txyz.ai	17
Total	**18,819**

III. CARBON EMISSION: STATE OF ART METHODS

The state of the art methods for carbon emission consist of a variety of cutting-edge technologies, strategies, and policies. In our review, we collected some methods that can help reduce carbon emissions in ML applications described below:

1) Carbon Neutrality: Carbon neutrality, also addressed by net zero carbon emissions, refers to the state in which an entity, such as an organization, individual, or even a whole country, emits no more CO_2 or other GHGs into the atmosphere than it removes from the atmosphere or offsets through measures like carbon sequestration or purchasing carbon credits. Achieving carbon neutrality involves reducing carbon emissions through energy efficiency improvements, renewable energy adoption, and other mitigation measures, while also actively removing carbon from the atmosphere through practices like afforestation, reforestation, and carbon capture and storage. The goal is to limit the concentration of GHGs in the atmosphere, thus helping to stabilize global temperatures and reduce the risks associated with natural disasters and ecosystem disruptions. Mishra and Singh [17] introduce a carbon neutral coefficient (CNC) as an indicator of the balance between carbon sequestration and emissions, aiming to guide manufacturers towards carbon neutrality.

TABLE IV
THE QUALITY ASSESSMENT QUESTIONS FOR THE INCLUSION OF A PAPER

ID	Quality Assessment Questions
QAQ1	Is a paper related to current ML methodologies?
QAQ2	Is the experiment related to ML or its sustainability?
QAQ3	Is the method validated by real-world experiment or done with conceptual models?
QAQ4	Is the study supported by ML research?
QAQ5	Are the limitations of study analyzed explicitly?
QAQ6	Is the proposed publishing method compared with other existing methods?

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2) Carbon Dioxide Equivalent: Carbon dioxide equivalent (CO_2eq) denotes the unit of measurement of CO_2 emissions with the global warming potential. It is a metric which is used to express the various greenhouse gases in terms of the equivalent amount of CO_2. Since different GHGs have different effects on heat trapping and their lifespans in the atmosphere differ, CO_2eq provides a standardized measure to compare and aggregate emissions from various sources. The CO_2eq is calculated by following equation:

$$\mathrm{CO_2}eq = E * C \tag{1}$$

In equation 1, E represents the quantity of electricity used during any computational procedure measured in kilowatt-hours (kWh) and C is the amount of CO_2 emitted from producing one of given unit of electricity.

3) Carbon Accounting: Carbon accounting is the method used to measure the emission by an organization, activity, product, or individual to assess their environmental impact and establish targets to reduce emissions. It involves quantifying the emissions associated with various activities to make a report of these emissions in standardized units such as CO_2eq. Carbon accounting is a critical tool for addressing climate change, driving emissions reductions, and promoting sustainable development. It provides the foundation for informed decision-making, an effective climate, and a low-carbon future [18].

4) Carbon Credit: Carbon credit is a system where entities can earn credits by reducing their GHGs, thereby incentivizing emission reductions and fostering a transition to a low-carbon economy. If a company reduces its emissions below its allocated limit, it can sell its excess credits to other companies that exceed their limits; these credits can then be traded or sold to other entities that need to offset their emissions [19].

5) Carbon Offsetting: Carbon offsetting is a mechanism used to compensate for CO_2 emissions generated by an individual, organization, or activity by investing in projects or activities that reduce or remove an equivalent amount of CO_2 from the atmosphere. People often use carbon offsetting as a complementary strategy to direct emissions reduction efforts, particularly for emissions that are challenging to avoid or completely eliminate. While carbon offsetting can help individuals and organizations take immediate action to address their carbon footprint, it is crucial to reduce emissions at the source through efficiency, adaptation of renewable energy, and sustainable approaches [20].

6) Life-cycle Assessment: A life-cycle assessment (LCA) is a systematic process for evaluating the environmental impacts of a product, process, or activity throughout its life cycle, from raw material preparation to product disposal. The analysis can aid product stakeholders in comprehending the environmental importance of natural resource utilization and environmental discharges [21]. Ligozat et al. [21] proposed that LCA should be integrated with every AI services. Analyzing the carbon emission in entire life cycle of products or systems, LCA can help to minimize unintended environmental consequences and promote more sustainable consumption and production patterns [22].

7) Representative Concentration Pathway: Climate scientists and researchers use representative concentration pathways (RCPs) to explore possible future trajectories of greenhouse gas emissions that affect the Earth's atmosphere providing an overview of the earth's temperature. The RCPs cover a wide range of possible future carbon emission trajectories, with RCP2.6 representing a very low emissions scenario that achieves significant reductions, RCP4.5 and RCP6 representing medium stabilization scenarios, and RCP8.5 representing a high baseline emissions scenario. It also provides a comprehensive overview of climate change to facilitate climate research and assessment [23].

8) Replacement Rate in Sustainability: The replacement rate in sustainability typically refers to the rate at which renewable or sustainable resources are replenished or replaced after being used or consumed. It is a critical concept in evaluating the sustainability of practices, products, or systems. For example, in forestry, the replacement rate might refer to how quickly trees are replanted and grown to replace those harvested for timber. In agriculture, it could refer to the rate at which crops are replanted and harvested in a manner that maintains soil fertility and ecosystem health. In broader terms, it can also apply to energy sources, such as the rate at which renewable energy like solar power, wind power, etc. is generated compared to the rate at which it is consumed. In short, a sustainable replacement rate ensures that resources are used at a pace that allows them to be replenished naturally or through human intervention, without depleting them or causing long-term harm to the environment [24], [25].

9) Environmental Impact Assessment: Environmental impact assessment (EIA) focuses on identifying and evaluating the possible environmental impacts of a project, development, or policy before it is realized. The primary objective of an EIA is to assist decision-makers in considering the environmental consequences of their actions and making informed choices that promote sustainable development and minimize adverse environmental effects. EIA is an essential tool for promoting sustainable development, preventing environmental degradation, and fostering responsible decision-making in various sectors such as infrastructure development, energy projects, urban planning, and natural resource management [26].

10) Carbon Budget: Carbon budgeting is a process that measures how much carbon dioxide is produced from different industries, homes, and other emission sources and how to reduce the emissions. An accurate carbon budget can help us project emissions, take appropriate measures to prevent a rise in global temperature, and achieve net-zero carbon emissions. Reducing global temperature rise is a challenge, as temperatures cannot exceed more than 1.5°C to 2°C. If the temperature rises above this level, the world will face different catastrophes, like natural disasters, a rise in sea level, and a reduction in natural resources. To avoid these emissions, several policies and agencies enforce the carbon emission budget [27].

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IV. Potential ML Responsible for Emission

In general, ML requires computation, which uses energy and creates emissions [28]. Henderson et al. [29] suggested that floating point operations are the main reason for this emission. In addition to floating-point operations, numerous analyses employ ML to investigate the various ML paradigms that contribute to this emission.

1) Industrial ML Emission: The study conducted by Zhang et al. [30] primarily concerned with the computation and analysis of carbon emissions and they introduced "The logarithmic mean divisia index" decomposition approach. It employed to ascertain the primary determinants of industrial carbon emissions, encompassing ML energy consumption, energy structure, industrial structure, economic efficiency, and staff population size. The findings indicate that the rise in industrial carbon emissions is mostly attributed to economic efficiency, but energy efficiency acts as the principal determinant in mitigating emissions. Furthermore, the researchers discovered that industries with high carbon content play a substantial role in facilitating the rise of emissions, whereas industries with medium and low carbon content have a more effective impact on limiting carbon emissions. Another research done by Munsif et al. [31] offered a valuable information for the government to modify the industrial infrastructure, manage excessive production capacity, and attain the objective of reducing carbon emissions. Furthermore, it suggested that the reduction of industrial pollution necessitates a comprehensive strategy that encompasses the implementation of cleaner technology, energy efficiency measures, fuel substitution, and efficient emission control techniques.

2) Federated Learning: Federated learning (FL) is one of the popular decentralized ML techniques where model training is performed on multiple local devices or local servers without sharing the local data to other devices [32]. Similarly, FL and other distributed ML also have carbon emission problem [33]. Recently, Qiu et al. [34] showed the emission issue of the FL approach by comparing the carbon footprint of FL to that of traditional centralized ML learning methods.

3) Differential Privacy: Differential privacy (DP) is a technique that aims at safeguarding the privacy of data. The goal of DP is to prevent the disclosure of any personally identifiable information (PII) regarding individuals when responding to queries [35]. Naidu et al. [36] demonstrated that DP has an impact on the carbon footprint and demonstrate that adding noise to preserve privacy can significantly increase the energy consumption and carbon emissions of the models through extensive experiments on NLP, image classification, and reinforcement learning tasks. They also observe that models with stronger privacy guarantees require more computational resources and training time to achieve the same performance as non-private models, leading to a higher carbon footprint. So, these provided quantitative insights on the trade-off between privacy and environmental impact, highlighting the need to consider the climate implications of privacy-preserving ML algorithms.

4) ML Configuration: The rapid growth of ML technologies has raised concerns about their significant carbon emissions due to high computational requirements [37]. By mapping these configuration to a sustainable framework, the study fosters greater awareness and encourages responsible practices in ML development. The findings reveal that the training phase contributes the most to carbon emissions, and the selection of hyperparameters, such as the optimizer, number of training [38] and number of layers, can significantly impact carbon emission specifically in large DNN [28], [39]. Research is going to make energy and performance optimized neural network architecture [40].

5) Large Language Models and Generative AI: Large Language Models (LLMs) have raised concerns regarding sustainability due to their significant environmental impact and high computational costs associated with training and fine-tuning these models [41]. The environmental and financial costs of large LLMs have been highlighted in various studies, emphasizing the need to address sustainability challenges in the development and deployment of LLMs [42], [43]. For example, the final training of BLOOM, a large language model emitted approximately 24.7 tonnes of CO_2eq considering the dynamic power consumption, and 50.5 tonnes if accounting all processes ranging from equipment manufacturing to energy-based operational consumption [44].

Several studies have been conducted [44]–[48] to evaluate the performance of these models and their carbon footprints. Researchers have pointed out that the training of high-performance models poses sustainability issues, as it is not always clear how these models should be retrained or fine-tuned to improve performance without incurring excessive environmental costs [49], [50]. The scale of LLMs and the resources required for their training have been identified as key factors contributing to their sustainability challenges [51], [52]. Efforts are being made to explore sustainable scaling strategies for LLMs, considering environmental, regulatory, and ethical requirements to mitigate their impact on the environment and ensure long-term sustainability. Researchers have been investigating on methods to optimize training processes and model sizes to achieve compute-optimal LLMs, which could help address sustainability concerns associated with LLMs encompassing environmental considerations, computational efficiency, and ethical implications to ensure the responsible development and deployment of these powerful language models [53], [54]. Researcher are focusing towards pre-trained language models to save computation helping the sustainability.

Generative AI (genAI) extends the LLM, which is capable of producing new content like images, text, or music based on patterns learned from vast datasets. The genAI, power-hungry AI models pertain to a large carbon footprint associated with training and deploying. Sustainable practices in genAI encompass optimizing algorithms for efficiency, promoting transparency and accountability in their deployment, and fostering collaboration across interdisciplinary fields to address emerging challenges and opportunities while minimizing negative impacts on society and the environment. Currently, researchers are focusing on reducing genAI inference emission [55].

6) Cloud Computing: The increasing need for cloud infrastructure has substantially heightened the energy consumption of data centers, raising significant concerns. This excessive energy usage not only leads to higher operational costs, thereby reducing the profit margins of cloud providers, but also contributes to heightened carbon emissions, posing serious environmental risks [56].

7) Cryptocurrency Mining: ML are now extensively used with the cryptocurrency [57]. Fadeyi et al. [58] examined the sustainability challenges posed by the energy-intensive nature of cryptocurrency mining, particularly in the context of smart cities. The authors noted that the significant electricity consumption of processes like Bitcoin mining, estimated to potentially equal the usage of entire countries, poses a threat to efforts to mitigate climate change and achieve sustainability goals. While cryptocurrencies and blockchain technology present potential benefits, the authors argued that current regulatory frameworks in most nations inadequately address the environmental impact of mining activities. Rather than outright bans, the research suggested exploring more energy-efficient consensus mechanisms and policy interventions, such as taxation, renewable energy incentives, and smart grid infrastructure, to better manage the energy usage of cryptocurrency operations. The authors emphasized the need for further research to accurately model and measure the energy consumption of mining in order to inform effective policymaking and technological solutions that can retain the utility of cryptocurrencies while addressing their sustainability challenges [59].

V. Quantification Methods

ML researchers [38], [69] also suggested that carbon emission by ML fluctuated with time, other tried to curb emission by providing benchmark of different ML models. AlShafeey et al. [70] put more emphasis on carbon quantification. By quantification, government and policymakers can evaluate carbon emissions by carbon pricing and deduce a sustainable energy policy [71], [72].

Table V provides an overview of the various quantification methods and tools available for measuring the carbon footprint of ML and related computational tasks. These methods range from cloud-specific tools to general-purpose frameworks for ML research. By presenting these quantification methods in a structured manner, starting with the overview table and followed by detailed descriptions, readers can quickly grasp the landscape of available tools before diving into the specifics of each method. This approach enhances the clarity and accessibility of the information, making it easier for researchers and practitioners to identify and implement suitable tools for measuring and reducing the carbon footprint of their ML projects.

A. Cloud Carbon Footprint

Cloud carbon footprint is an open-source initiative focused on quantifying and mitigating the environmental impact of cloud computing. Through the development of tools and methodologies, the project endeavors to raise awareness and provide practical solutions for measuring and reducing carbon emissions associated with cloud-based services and applications. By employing industry-standard models and algorithms, cloud carbon footprint enables users to estimate the carbon footprint of their cloud usage, taking into account factors such as energy consumption, data center locations, and server utilization. As an open-source endeavor, the project fosters collaboration among developers, researchers, and environmental advocates, promoting continuous improvement and broader adoption of sustainable practices in the IT industry and source code can be found on GitHub [60].

B. Tracarbon

Tracarbon is an open-source initiative that aims to quantify and analyze the carbon emissions associated with software development processes and infrastructure operations. Through the provision of tools and utilities, Tracarbon facilitates the measurement of carbon footprints in software projects and infrastructure deployments, contributing to heightened awareness of the environmental impacts of such practices. Tracarbon seamlessly integrates with development workflows and infrastructure monitoring tools, facilitating the collection of data on energy consumption and resource usage, which it then uses to calculate carbon emissions. Emphasizing sustainability in software development, Tracarbon encourages community collaboration and encourages contributions to enhance its functionality and applicability within the realm of sustainable software development through this open-source endeavor. The source is available on GitHub [61].

C. Green Algorithms

Green Algorithms [62] is an online tool that estimates and reports the carbon footprint of computational tasks in a standardized and reliable way. The framework considers various factors such as hardware requirements, runtime, and geographic location to calculate the greenhouse gas emissions associated with connecting sustainability with other economic aspects. It is available in GitHub [63].

D. Eco2AI

Eco2AI is another library written in Python which helps data scientists and researchers to estimate the energy consumption and CO_2eq emissions of ML models. This library focuses on accurate tracking of energy consumption by accounting for the power usage of CPU, GPU, and RAM devices, as well as regional CO_2 emissions factors. The author claimed that Eco2AI have a dedicated data of emission intensity coefficients for 365 global regions, enabling precise estimation of the carbon footprint associated with model training and inference. By providing this tool, the authors aim to motivate the research community to search for more computationally efficient AI architectures, aligning with the principle of sustainable AI and contributing to the broader goals of reducing the environmental impact of AI [64].

TABLE V
QUANTIFICATION METHODS FOR SUSTAINABLE ML.

Method	Description	Key Features
Cloud Carbon Footprint [60]	Open-source initiative for cloud computing	- Estimates carbon footprint of cloud usage - Considers factors like energy consumption and data center
Tracarbon [61]	Open-source tool for software development	- Measures carbon footprints in software projects - Integrates with development workflows
Green Algorithms [62], [63]	Online tool for computational tasks	- Estimates GHG emissions for specific computations - Contextualizes emissions in terms of travel distance
Eco2AI [64]	Python library for ML models	- Tracks energy consumption of CPU, GPU, and RAM - Uses regional CO_2 emissions factors
ML CO_2 Impact [65]	Tool for neural network training	- Considers server location, energy grid, and hardware - Provides actionable steps for mitigation
Carbontracker [66]	Open-source tool for deep learning	- Tracks energy consumption and carbon emissions - Supports predictions for training duration and footprint
Experiment Tracker [29]	Framework for ML research	- Tracks real-time energy usage and carbon intensity - Generates standardized online appendices
EnergyVis [67]	Interactive tool for ML models	- Visualizes and compares model energy consumptions - Explores different deployment locations and hardware
CodeCarbon [68]	Python package for software applications	- Measures carbon emissions of computational resources - Designed for organizations and individuals

E. ML CO_2 Impact

Lacoste et al. [65] addressed the environmental impact of training neural networks in ML and create the ML CO_2 Impact tool. The tool emphasizes key factors influencing carbon emissions in ML training, such as server location, energy grid, training duration, and hardware used by introducing this emissions calculator, we can estimate carbon emissions and provide actionable steps to mitigate environmental impact.

F. Carbontrcaker

Carbontracker is an open-source tool developed to track the energy consumption as well as carbon emissions associated with training deep learning models. The authors emphasized the growing environmental impact of the increasing compute demands in deep learning and proposed that reporting energy and carbon footprint alongside performance metrics can promote responsible computing, incentivize research into energy-efficient neural network architectures, and support predictions of the total training duration, energy usage, and carbon footprint, enabling users to proactively monitor and mitigate the environmental impact. The authors provided the experimental results demonstrating the tool's accuracy in tracking power consumption across GPU, CPU, and memory components and discussed strategies for reducing carbon emissions, such as leveraging regions with low-carbon electricity grids, optimizing training schedules, and employing energy-efficient algorithms and hardware [66].

G. Experiment Impact Tracker

The experiment impact tracker (EIT) is a flexible framework developed to facilitate the reporting of energy consumption and carbon emissions for ML research. EIT provides a simple user interface for tracking real-time energy usage, carbon intensity, and other computational metrics, while generating standardized online appendices to enable consistent and transparent reporting. The modular design allows the community to extend the framework's capabilities, and features like reproducibility logging and fault tolerance ensure the data is reliable. By making it easier to account for the energy and environmental impacts of ML experiments, the Experiment Impact Tracker aims to drive more sustainable practices, such as incentivizing energy-efficient algorithms, shifting computations to low-carbon regions, and carefully weighing the trade-offs between model performance and energy costs [29].

H. EnergyVis

The EnergyVis tool is a user-friendly software that enables the interactive measurement and monitoring of energy use in ML models. This software can monitor, provide visual representations of, and compare the energy usage of models from various perspectives. The system prioritises important measurements like as kWh and CO_2eq emissions, enabling users to investigate various deployment sites and hardware choices in order to minimise their carbon footprints. Its main objective was to increase awareness of sustainability by visually highlighting the high energy and low computational requirements during model training through the proposal of alternative training approaches to reduce energy consumption [67].

I. CodeCarbon

CodeCarbon is a lightweight open source Python software package that allows developers to measure and track the carbon emissions associated with the computational resources used by their software applications. It is designed to help organizations and individuals quantify the environmental impact of their software development and deployment practices [68].

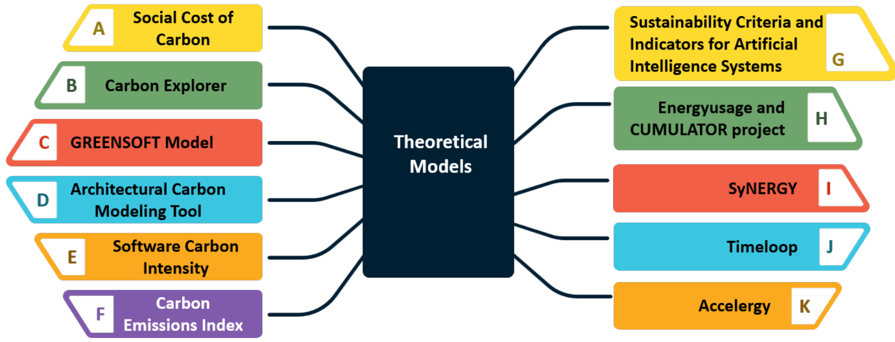

Fig. 4. The list of all theoretical models for carbon emission.

VI. Theoretical Models

Besides the quantification of ML emissions, there is some theoretical background that can assess a sustainable approach to evaluating emissions. Sustainability is becoming a buzzword [73] and the new civilization should connect sustainability with other economic aspects like poverty and unemployment [74]. In Figure 4, we describe some economic and conceptual frameworks in sustainability in following parts:

A. Social Cost of Carbon

The Social Cost of Carbon (SCC) refers to the dollar value of future economic damage caused by every extra ton of CO_2 released to the atmosphere [75]. It's a way to express the harm from climate change in dollars and it is estimated by the Dynamic Integrated Model of Climate Economy (DICE) that translates the long-term economic damages of climate change into present-day dollar values [76]. However, the discount rate reflects the societal time preference, significantly influences the SCC. A higher discount rate prioritizes near-term benefits, lowering the SCC and potentially undervaluing future climate burdens. This economic metric and its dependence on the discount rate are central to analyzing climate change policy and the ongoing debate surrounding the economic justification for immediate climate action [77].

B. Carbon Explorer

Acun et al. [78] proposed Carbon Explorer, an exploration framework that takes a holistic approach to achieve carbon-free computing in cloud datacenters by 24/7. This framework figures out the best mix of different types of renewable energy, energy storage, and carbon-aware computation shifting by looking at renewable energy sources and how available they are for different patterns of datacenter power demand. The framework takes a holistic approach, balancing the reduction in operational carbon footprint against the increase in embodied carbon costs associated with the deployment of additional infrastructure.

C. GREENSOFT Model

The GREENSOFT Model is a conceptual reference model that promotes the development, maintenance, and use of environmentally friendly and sustainable software. It also includes software from the beginning until the end of its life, sustainability metrics and criteria, procedure models for different stakeholders, and recommendations and tools that assess the software's direct and indirect impacts. The key aspects of this model include definitions of green and sustainable software engineering, a life cycle analysis approach, and the incorporation of common software quality criteria alongside sustainability-specific metrics [79].

D. Architectural Carbon Modeling Tool

Architectural carbon modeling tool (ACT) is another architectural carbon modeling tool which enables carbon-aware design exploration for computer systems. The ACT tool comprises an analytical, extensible model that estimates the embodied carbon emissions from manufacturing hardware components such as processors, memory, and storage, as well as the operational carbon emissions during system use. ACT leverages public data and industry reports on semiconductor fabrication characteristics to quantify the carbon footprint of hardware across the complete life cycle. The model enables researchers to explore sustainability-driven optimization targets, such as carbon-delay product and carbon-energy product, which can yield distinct hardware design choices compared to traditional performance, power, and area optimization approaches [80].

E. Software Carbon Intensity

The Green Software Foundation has devised a metric called software carbon intensity (SCI) that quantifies the rate of carbon emissions per functional unit. The equation utilized to compute the SCI is:

$$SCI = ((E \times I) + M) \tag{2}$$

where E denotes the energy consumption attributed to a software system, with a specific emphasis on the energy utilization of Graphical Processing Units (GPUs), quantified in kWh. These emissions are measured in grams of carbon dioxide equivalent per kilowatt-hour (gCO_2eq/kWh), as provided by WattTime. M symbolizes "embedded carbon" which represents the carbon emissions generated during the inception, operation, and disposal phases of a hardware device's lifecycle. It

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focused on the location-based marginal carbon emissions associated with the electrical grid powering the datacenter [81].

F. Carbon Emissions Index

The carbon emissions index (CEI) is a metric used to measure the total amount of CO_2 with other GHGs emitted by a company, sector, or country, expressed as a percentage of their total emissions which includes direct emissions, indirect emissions such as purchased electricity, other indirect emissions, and emissions from sources not directly owned or controlled by the entity but related to its activities, such as employee travel, waste disposal, or the use of sold products. Investors, policymakers, and environmental organizations often use the CEI to assess the carbon footprint of companies or sectors and to make informed decisions about investments, regulations, or advocacy efforts. It can also be used by companies themselves to track their own emissions, set reduction targets, and implement strategies to mitigate their environmental impact. The CEI is typically expressed in grams of CO_2eq emitted per kilowatt-hour of electricity generated. A higher CEI value indicates that the electricity generation in that region or country has higher associated CO_2 emissions, primarily due to a greater reliance on fossil fuels like coal and natural gas. A lower CEI implies that the electricity is generated from cleaner sources with lower or negligible CO_2 emissions, such as nuclear, hydroelectric, or other renewable sources [82].

G. Sustainability Criteria and Indicators for Artificial Intelligence Systems

Rohde et al. [83] proposed the sustainability criteria and indicators for artificial intelligence systems (SCAIS) framework which contains 19 sustainability criteria for sustainable AI development and 67 indicators that were based on the results of a critical review and expert workshops. SCAIS aims to help researchers and policymakers explore ways to incentivize the development and adoption of green AI.

H. Energyusage and CUMULATOR project

Energyusage, an open-source Python package that calculates the energy consumption and carbon dioxide emissions associated with running a given computational function. The package uses the running average power limit interface on Intel processors to directly measure energy usage, and then contextualizes these measurements by determining the local electricity grid composition and emissions factors. They demonstrate the utility of these reports by analyzing the energy-accuracy trade-offs for several common ML models, finding that energy usage is a distinct and important consideration beyond traditional performance metrics. The work aims to empower computer scientists to take an active role in environmental sustainability through more energy-efficient algorithm design [84].

The CUMULATOR project was built to raise awareness about the environmental impact of ML methods and encourage their optimization. It is an open-source API that calculates the carbon footprint of ML that integrates the project into the Alg-E platform to analyze the trade-off between model's accuracy and carbon footprint. Additionally, the project also created a protocol named carbon impact statement, which helps users quantify the carbon footprint of their projects with the goal of incorporating climate change considerations into academic research and promoting environmentally conscious practices in the field of ML [85], [86].

I. SyNERGY

SyNERGY is an innovative energy measurement and prediction framework designed specifically for Convolutional Neural Networks (ConvNet). This framework addresses the lack of energy measurement support in current deep learning frameworks, such as Caffe and TensorFlow, by providing comprehensive tools for both overall and fine-grained per-layer energy measurements. Moreover, it introduces a sophisticated energy prediction model that utilizes performance counters, including the number of executed SIMD instructions and bus accesses, to accurately estimate the energy consumption of convolutional layers within a ConvNet [87].

J. Timeloop

Timeloop [88] is a structural framework used to assess and investigate the architecture and design possibilities of DNN accelerators. The proposed approach offers a fundamental structure and implementation characteristics of DNN accelerators. It aims to describe a wide range of hardware topologies and simulate these topologies to produce precise predictions of performance and energy efficiency for a DNN workload which is achieved by utilizing a mapper that determines the most efficient method for scheduling operations and staging data on the designated architecture. Fair comparisons across various architectures are facilitated, hence enhancing the systematic design of DNN accelerators and energy efficiency.

K. Accelergy

Accelergy [89] is an another architecture-level energy estimation tool for DNN accelerators which is a generally applicable energy estimation methodology for accelerator designs. It enables fast design space exploration at the architecture level. It also allows users to describe hardware designs using user-defined graphical components. This methodology addresses the challenges associated with accurately estimating the energy consumption of diverse accelerator designs, which are sensitive to data patterns and often employ components not found in conventional processors.

VII. Intersection of ML Security and Emission

The environmental sustainability of ML systems should be considered along with efficiency, as efficiency alone is not enough to fully remedy the environmental impacts of ML. Wright et al. [90] demonstrated three key discrepancies that illustrate the complexity of the relationship between efficiency and sustainability in ML: compute efficiency does not always translate to energy or carbon efficiency, efficiency can have unexpected effects on operational emissions across the ML model life cycle, and efficiency does not account for, and can potentially exacerbate, the broad environmental impacts from hardware platforms.

A. Layer Sustainability Analysis

Layer sustainability analysis (LSA) is a framework that focuses on analyzing vulnerabilities in deep neural networks (DNN) for adversarial attacks. It aims to assess the sustainability and vulnerability of model layers by monitoring and analyzing their behavior against adversarial inputs. LSA identifies the most vulnerable layers in a neural network by evaluating the sustainability of each layer through comparative measures, such as relative error. The framework utilizes Lipchitz continuity to gain deeper insights into the sustainability analysis of neural network models, emphasizing the importance of layer-wise analysis. By identifying and addressing the vulnerabilities in different layers, LSA contributes to improving the robustness and generalization of the network [91].

B. Robustness Carbon Trade-off Index

Hasan et al. [92] introduced the Robustness Carbon Trade-off Index (RCTI), a novel metric that quantifies the trade-off between enhancing the resilience of adversarial ML models and the associated carbon footprint. The main idea of this research is to address the environmental impact of adversarial ML, specifically focusing on the carbon emissions generated by improving model robustness against adversarial training. By examining this relationship through experiments on evasion attacks, they aimed to highlight the importance of considering environmental sustainability alongside security in the design of ML systems. They further extend this study to measure the cost by proposing Cost Per Unit of Robustness Change (CRC) which merges SCC to calculate the value in terms of monetary values [93].

VIII. Possible Solutions of ML emission

We outlined various strategies to address ML's carbon emissions and environmental impacts from current literature. The main points are:

A. Renewable Energy

Energy sector creates a lot of GHGs [94]. Green renewable energy systems encompass technologies that harness natural resources like sunlight, wind, water, geothermal heat, and biomass to generate electricity with minimal environmental footprint. These systems offer a sustainable alternative to traditional fossil fuel-based energy sources by reducing greenhouse gas emissions and mitigating the depletion of finite resources. While each technology has its own advantages and limitations, a combination of these renewable sources can create a diverse and reliable energy portfolio, fostering a more sustainable energy future [95], [96].

B. Sustainable Cloud Computing

Sustainable cloud computing refers to the practice and utilization of cloud computing resources in an environmentally friendly and energy-efficient manner in order to minimize the impact on the environment while maximizing operational efficiency and reducing costs. Sustainability is interconnected with cloud computing have gained significant attention in recent years due to shift towards cloud. One key aspect of sustainable cloud computing is the implementation of energy-efficient techniques. Researchers have developed innovative solutions such as holistic resource management to address the global challenge of reducing operational costs and enhancing service sustainability within cloud computing systems [97]. These techniques focus on optimizing resource utilization, consolidating services, and improving overall energy efficiency. Additionally, Feroz et al. [98] proposed the development of IoT-based cloud integrated solutions, such as smart classrooms and smart agriculture systems, demonstrating the potential for leveraging cloud computing to create sustainable environments. These systems utilize IoT sensors, data analytics, and cloud infrastructure to optimize resource usage, improve productivity, and reduce environmental impact. Moreover, the integration of technologies like IoT and AI in cloud computing plays a crucial role in promoting sustainability. By leveraging IoT devices and cloud computing services, organizations can achieve better resource management, data analytics, and decision-making processes, leading to more sustainable practices [99].

C. Smart Grid and Energy System Optimization

Smart grid and its components use different ML models, such as demand-response algorithms, to facilitate the development and integration of sustainable energy systems into the smart grid [100], [101]. For instance, the adoption of electric vehicles, Vehicle-to-Grid (V2G) will contribute to sustainability in future with reduced emissions [102], [103].

D. Green Computing

Green computing, encompassing sustainable IT practices, refers to the design, manufacturing, utilization, and disposal of computers and related technologies with a focus on minimizing environmental impact. This multifaceted approach targets reduced energy consumption, minimized e-waste generation, improved energy efficiency throughout the lifecycle, integration of renewable energy sources, and overall resource conservation [104]. Green computing practices implemented throughout a computer's lifecycle, from design and manufacturing to use and disposal, contribute significantly to environmental sustainability efforts. Emphasis should be given on both hardware and software level. For a green environment, the hardware should "go green" for protecting us from hazardous environmental consequences [105], [106].

E. Model Compression

Model compression techniques of ML helps to reduce the size and complexity of ML models, improving their efficiency and deployability to help energy-efficient inference [107]. Techniques like pruning [108], [109], ML quantification on configuration [110], discrete rank pruning [111], knowledge distillation [112], etc. can help contribute to sustainability by adaptive design of model architectures to optimize energy efficiency.

F. Carbon-aware Design

Carbon-aware design is an approach to designing products, systems, buildings, or processes with a primary focus on minimizing carbon emissions and reducing the overall carbon footprint throughout the entire lifecycle. Moro et al. [113] proposed Carburacy, the first carbon-aware accuracy measure that evaluates ML models based on both their effectiveness and ecological sustainability. The authors stated the Carburacy as a novel evaluation metric that captures the trade-off between a model's performance and its carbon emissions, enabling the research community to develop more environmentally friendly state-of-the-art models. Through an in-depth benchmark study on long document summarizing tasks under low-resource regimes, the authors identified optimal hyperparameter combinations that allow models to achieve high effectiveness with significantly lower carbon costs. The findings highlight the importance of considering environmental impact alongside traditional performance metrics and demonstrate the applicability of Carburacy across various natural language processing tasks, paving the way for more sustainable advancements in AI research.

G. Energy-efficient Algorithms

Memmel et al. [114] proposed Tensor networks (TNs) as a promising tool for sustainable and efficient AI. TNs have the capability to reduce computation significantly without compromising accuracy, addressing the exponentially growing demand for computation in AI research. The authors demonstrate efficiency gains achieved by integrating TNs into kernel machines and deep learning models, showing that TNs can enable logarithmic compression, reducing the computational complexity from exponential to linear in the dimensionality of the data. The authors argued that better AI algorithms should be evaluated based on both accuracy and efficiency, and they discussed various efficiency metrics, such as CO_2 emissions, electricity usage, and floating-point operations, to quantify the sustainability and progress of AI algorithms. Overall, the paper highlighted the potential of TNs to contribute towards green AI by making AI algorithms more efficient, thus positively impacting the economic, social, and environmental dimensions of sustainability. Similarly, He et al. [115] proposed automated machine learning (AutoML), which is another initiative for an energy efficient ML approach.

H. Transfer Learning

Transfer learning significantly enhances sustainability efforts by enabling models to apply knowledge acquired from one task to improve performance on another. This approach substantially increases efficiency, accuracy, and sustainability across various applications [116]. Notable examples of transfer learning architectures include LeNet-5, AlexNet, VGG16, Inception-v3, and ResNet. In healthcare, leveraging pre-trained models from large datasets like ImageNet allows for more efficient learning on smaller medical imaging datasets, resulting in improved diagnostic accuracy, reduced costs, and more sustainable healthcare practices. Recent applications have extended to smart building management, where transfer learning algorithms optimize electricity dispatch, enhance energy efficiency, and promote overall sustainability [117].

I. Big Data Analysis

The rapid growth of big data and advanced analytics, including ML techniques, has the potential to transform climate change mitigation research and practice. Large-scale, high-resolution datasets from remote sensing, digital platforms, and sensor networks can provide unprecedented insights into the spatial patterns and determinants of urban energy use, greenhouse gas emissions, and mitigation opportunities. ML algorithms can extract meaningful insights from these diverse data sources, enabling researchers to move beyond generic, top-down recommendations and develop tailored, context-specific solutions for low-carbon transitions in buildings, transportation, and urban planning [118]. By integrating big data analytics into climate mitigation frameworks, the research community can generate more accurate, scalable, and actionable strategies to support sustainable urban development [119], urban transportation [120], etc.

J. Sustainability of Cryptocurrency: Green Coin

Cyrptocurrency is moving toward sustainability [121]. For instance, Green Coin [122] is a cryptocurrency that aims to promote environmental sustainability and green initiatives through its blockchain-based platform. GreenCoin is designed to incentivize and reward individuals and organizations for engaging in eco-friendly practices, such as reducing carbon emissions, supporting renewable energy projects, and participating in conservation efforts.

K. Sustainable Electric Vehicle

The transportation sector has the highest impact of producing GHG emissions [123]. To address this issue, sustainable electric vehicles (EVs) are essential to consider with other aspects such as their environmental impact, supply chain sustainability, battery life cycle, and policy implications [124]. Compared to traditional combustion engine vehicles, EVs are often seen as a more environmentally friendly alternative due to their potential to reduce carbon emissions and contribute to a cleaner transportation sector [125]. Thus, the adoption of EVs plays a crucial role in promoting sustainability in the transportation sector. Studies have highlighted the importance of understanding the factors influencing the adoption of EVs and the overall sustainability consequences associated with this transition. Consumer adoption intention for electric vehicles is a key aspect that can drive the demand for sustainable transportation solutions. The sustainability of electric vehicles also extends to the battery technology used in these vehicles. The development of sustainable business models for electric vehicle battery second use is gaining attention as a way to maximize the value of batteries and reduce waste in the supply chain. Countries like China have implemented evolutionary policy incentives to support the development of EVs in alignment with environmental sustainability goals. Furthermore, the longevity of electric vehicle operations and the potential for cost reductions through sustainable practices are key factors in transitioning towards a more sustainable and electrified future. Thus, sustainable EVs encompass a wide range of considerations, from environmental impact and adoption to battery technology, supply chain sustainability, policy incentives, and recycling practices, which can move towards a sustainable future for the transportation sector [126].

L. Green ML

Green ML aims to optimize ML architectures by balancing performance with computational efficiency, carbon footprint, and interpretability. Pedrycz et al. [127] emphasize the need for green ML, considering environmental and social costs alongside performance. Ultimately, green ML would make a shift away from the performance-driven "red ML," which requires more energy, towards a more holistic approach that prioritizes efficiency, robustness, and environmental responsibility.

M. Green IoT

Arshad et al. [128] proposed green IoT to curb emissions in existing IoT. Green IoT means the use of eco-friendly technologies and practices to reduce the environmental impact of the IoT ecosystem. The key objectives of Green IoT are to minimize energy consumption, greenhouse gas emissions, and the use of non-renewable resources associated with IoT devices and infrastructure, especially building smart cities [129]. This involves the use of efficient hardware, energy-aware software, renewable energy sources, recycling and reuse strategies, and policies that promote sustainability [130], [131]. The goal is to develop IoT systems that are environmentally responsible and contribute to a more sustainable future, addressing the growing concerns about the carbon footprint of the rapidly expanding IoT landscape [132]. It aims to leverage technological advancements to achieve environmental conservation and preservation, aligning the progress of IoT with the broader objectives of sustainability [133]. Candanedo et al. [134] propose the use of an Edge-IoT platform along with a social computing framework to build a system aimed at smart energy-efficient IoT. This enable smart city to reduce data transfer from the IoT-Edge to the Cloud, thus helping sustainability by reducing cloud, computing, and network resource costs.

N. Green AI

Green AI refers to the concept of incorporating environmental considerations into artificial intelligence technologies, aiming to reduce energy consumption and minimize the environmental impact of AI systems. This approach advocates for the development of AI solutions that are more energy-efficient and environmentally friendly [135]. The idea of Green AI is gaining attention in research and industry as a way to address the growing concerns about the environmental footprint of AI technologies [136]. By promoting energy-efficient algorithms, hardware, and practices, Green AI aims to make AI more sustainable and reduce its overall carbon footprint. While Green AI is an important aspect of sustainable technology development, it is essential to note that it is not the only consideration in the field of AI. Both Green AI and traditional AI sometimes referred to as Red AI have their own contributions to make, and it is crucial to strike a balance between environmental sustainability and technological advancement. By integrating green principles into AI research and development, we can work towards creating more eco-friendly and sustainable AI solutions for the future [137], [138]

O. Green Deep Learning

Green deep learning is an emerging research field that aims to develop energy-efficient deep learning models and techniques to reduce the computational and energy costs associated with large-scale DNNs. This field focuses on various approaches, such as designing compact network architectures, developing efficient training and inference strategies, and utilizing data more effectively. By addressing the substantial carbon footprint and resource requirements of modern deep learning models, green deep learning seeks to make deep learning more sustainable and accessible, improving its real-world deployment and promoting greater inclusivity in the research community. The ultimate goal is to yield novel and competitive results without compromising the environment or limiting the participation of researchers with limited computational resources by promoting energy-efficient technologies like model compression and knowledge distillation [139].

P. Green Federated Learning

Yousefpour et al. [140] proposed "Green FL" by optimizing its parameters, thereby making design choices to minimize carbon emissions consistent with current performance and training time. Abbasi et al. [141] proposed another approach named "FedGreen" supporting green federated computing. To make this paradigm sustainable, research is growing. For example, Guler et al. [142] suggested several training mechanisms to make energy-efficient use of FL in low-powered devices. Similarly, Savazzi et al. [143] proposed "Federated Edge Learning" for low-powered IoT communications to reduce energy consumption and emissions.

Q. Green Networking

Green networking refers to the concept of designing and implementing network technologies and infrastructure in an environmentally friendly and sustainable manner. This approach aims to reduce the carbon footprint and energy consumption of network operations while promoting ecological balance and

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conservation. The idea of green networking is closely related to the broader concept of green growth, which emphasizes sustainable development and environmental protection. By incorporating green principles into network architecture and technologies, organizations can contribute to a more sustainable and eco-friendly future. One key aspect of green networking is the use of energy-efficient technologies and practices to minimize power consumption and reduce greenhouse gas emissions. This can include the deployment of energy-efficient network equipment, the optimization of network operations to reduce energy waste, and the use of renewable energy sources to power network infrastructure. Furthermore, green networking can also encompass the integration of green spaces and natural elements into urban network infrastructure planning. By incorporating green infrastructure such as parks, gardens, and wildlife networks into urban areas, cities can enhance biodiversity, improve air quality, and create more sustainable and livable environments for residents [144].

R. ML Lifelong Learning

Parisi et al. [145] suggested developing ML systems that can continuously learn and adapt to new information and tasks, without catastrophic forgetting. This proposed approach not only can preserve energy but also contribute to sustainability.

S. Green Metrics and Digital Twins

Green Metrics and Digital Twins are two emerging concepts that are transforming industries. Green metrics refer to quantifiable measures used to assess and track environmental performance. On the other hand, digital twin (DT) is a virtual replica of a physical object, system, or process that uses real-time data and simulations to monitor, analyze, and optimize performance. DT leverages the Internet of Things (IoT), ML, and AI to enable predictive analytics, decision-making, and process improvements. Together, digital twins and green metrics, organizations can move toward more sustainable and efficient operations [146].

T. Ethical AI and Responsible AI

Ethical AI ensures that ML algorithms and models are developed and deployed in ways that uphold ethical principles, such as fairness, transparency, accountability, and sustainability [147]. This involves addressing ethical considerations in data collection, algorithm development, etc., mitigating potential harm to individuals or communities, and promoting inclusivity and diversity in AI development.

Responsible AI goes beyond ethics by addressing practical considerations like bias, discrimination, and privacy concerns. It refers to the development and deployment of AI systems in a manner that prioritizes ethical considerations, AI system fairness, accountability, transparency, and societal well-being [148]. Nakao et al. [149] defined responsible AI as AI systems that are transparent, reliable, safe, and take into account human values and context. Similarly, Yoo et al. [150] focus specifically on ensuring AI fairness through human-centered design. By integrating principles, practices, and policies into the design, development, and use of responsible AI, we ensure that AI systems align with human values and respect fundamental rights.

IX. LIMITATIONS

Although the goal of this review is to offer a thorough overview of sustainable ML, it is important to recognize its several limitations. This review's temporal scope (up to May 2024) and focus on English-language, peer-reviewed publications may not capture the most recent developments or global perspectives. The lack of standardized metrics for measuring environmental impact in sustainable ML posed challenges in comparing results across studies. The interdisciplinary nature of the field and rapid technological advancements make it difficult to fully capture all nuances and up-to-date practices, particularly from industrial applications where proprietary information is limited. Moreover, the reliance on PRISMA and bibliometric methodologies, while enabling transparency and reproducibility, inherently excludes unpublished or non-indexed industrial data, which may result in underrepresentation of real-world deployments. In our synthesis, methodological variations across studies necessitated some subjective interpretation. While comprehensive, our review could not exhaustively cover every sub-domain within sustainable ML, potentially leading to an uneven representation of the field's various aspects. Despite these constraints, we believe this review provides valuable insights into the current state and future directions of sustainable ML, while acknowledging areas for improvement in future reviews.

X. CONCLUSION

This comprehensive review of sustainable ML reveals a rapidly evolving field at the intersection of technological innovation and environmental responsibility. The analysis highlights an exponential growth in research output, reflecting the increasing urgency to address ML's ecological footprint. Significant advancements in carbon footprint quantification tools, energy-efficient algorithms, and green computing infrastructure demonstrate the field's progress. However, challenges persist in standardizing sustainability metrics and conducting comprehensive life-cycle assessments of ML systems.

Importantly, this review adopts an interdisciplinary lens—bridging computer science, environmental science, and sustainability studies—to provide a holistic understanding of sustainable ML. Such cross-disciplinary integration is essential for developing robust sustainability frameworks, enabling innovations that are not only technically sound but also ecologically responsible and socially impactful.

Future research directions include innovating energy-efficient algorithms for resource-intensive applications and exploring synergies between hardware and software optimizations. As ML deployment in critical systems increases, the demand for scalable, cost-effective, and environmentally friendly solutions becomes more pressing.

This review provides a foundation for future work, emphasizing the balance between ML's transformative potential

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and environmental responsibility. The path forward requires concerted efforts from researchers, practitioners, and policymakers to align ML advancements with broader sustainability goals. By addressing these issues, the field can move towards a future where technological advancement and environmental stewardship coexist, harnessing ML's power to solve global challenges while minimizing ecological impact.

REFERENCES

[1] R. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," *International Journal of Information Management*, vol. 53, p. 102104, 2020.

[2] Z. Yao, Y. Lum, A. Johnston *et al.*, "Machine learning for a sustainable energy future," *Nat Rev Mater*, vol. 8, pp. 202–215, 2023.

[3] 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, A. Luccioni, T. Maharaj, E. D. Sherwin, S. K. Mukkavilli, K. P. Kording, C. Gomes, A. Y. Ng, D. Hassabis, J. C. Platt, F. Creutzig, J. Chayes, and Y. Bengio, "Tackling climate change with machine learning," 2019.

[4] X. Li, "A comparative study of statistical and machine learning models on near-real-time daily emissions prediction," 2023.

[5] S. Rasp, M. Pritchard, and P. Gentine, "Deep learning to represent subgrid processes in climate models," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 115, pp. 9684 – 9689, 2018.

[6] J. Cowls, A. Tsamados, M. Taddeo, and L. Floridi, "The ai gambit: leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations," *Ai & Society*, vol. 38, pp. 283 – 307, 2021.

[7] X. Zheng, Y. Lu, J. Yuan, Y. Baninla, S. Zhang, N. C. Stenseth, D. O. Hessen, H. Tian, M. Obersteiner, and D. Chen, "Drivers of change in china’s energy-related co₂ emissions," *Proceedings of the National Academy of Sciences*, vol. 117, no. 1, pp. 29–36, 2020.

[8] A. Kadam, L. N. Vempaty, D. P. K. Melam, D. K. Vairavel, A. Deepak, and V. H. Patil, "Tackling climate change with artificial intelligence," *2023 6th International Conference on Contemporary Computing and Informatics (IC3I)*, vol. 6, pp. 1704–1711, 2023.

[9] L. Kaack, P. Donti, E. Strubell, G. Kamiya, F. Creutzig, and D. Rolnick, "Aligning artificial intelligence with climate change mitigation," *Nature Climate Change*, vol. 12, pp. 518 – 527, 2022.

[10] C.-J. Wu, R. Raghavendra, U. Gupta, B. Acun, N. Ardalani, K. Maeng, G. Chang, F. Aga, J. Huang, C. Bai *et al.*, "Sustainable ai: Environmental implications, challenges and opportunities," *Proceedings of Machine Learning and Systems*, vol. 4, pp. 795–813, 2022.

[11] D. Hershcovich, N. Webersinke, M. Kraus, J. A. Bingler, and M. Leippold, "Towards climate awareness in nlp research," 2022.

[12] S. Luccioni, Y. Jernite, and E. Strubell, "Power hungry processing: Watts driving the cost of ai deployment?" in *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, 2024, pp. 85–99.

[13] S. Giannelos, F. Bellizio, G. Strbac, and T. Zhang, "Machine learning approaches for predictions of co2 emissions in the building sector," *Electric Power Systems Research*, vol. 235, p. 110735, 2024.

[14] B. Masoomi, I. G. Sahebi, M. Ghobakhloo, and A. Mosayebi, "Do industry 5.0 advantages address the sustainable development challenges of the renewable energy supply chain?" *Sustainable Production and Consumption*, vol. 43, pp. 94–112, 2023.

[15] L. I. Meho, "Bibliometric analysis of obesity research in the united states," *Journal of the American Dietetic Association*, vol. 106, no. 1, pp. 119–125, 2006.

[16] D. Moher, D. G. Altman, A. Liberati, and J. Tetzlaff, "Prisma statement," *Epidemiology*, vol. 22, no. 1, p. 128, 2011.

[17] S. Mishra and S. Singh, "Carbon management framework for sustainable manufacturing using life cycle assessment, iot and carbon sequestration," *Benchmarking: An International Journal*, vol. 28, no. 5, pp. 1396–1409, 2021.

[18] K. Kiswanto, A. Hajawiyah, A. Harjanto, and E. Setyarini, "Twelve years research journey of carbon accounting," *International Journal of Energy Economics and Policy*, vol. 13, pp. 246–254, 07 2023.

[19] N. Lokuge and S. Anders, "Carbon-credit systems in agriculture: a review of literature," *The School of Public Policy Publications*, vol. 15, 2022.

[20] H. Lovell and D. Liverman, "Understanding carbon offset technologies," *New Political Economy*, vol. 15, no. 2, pp. 255–273, 2010.

[21] A.-L. Ligozat, J. Lefevre, A. Bugeau, and J. Combaz, "Unraveling the hidden environmental impacts of ai solutions for environment life cycle assessment of ai solutions," *Sustainability*, vol. 14, no. 9, p. 5172, 2022.

[22] S. M. Moni, R. Mahmud, K. High, and M. Carbajales-Dale, "Life cycle assessment of emerging technologies: A review," *Journal of Industrial Ecology*, vol. 24, no. 1, pp. 52–63, 2020.

[23] D. P. Van Vuuren, J. Edmonds, M. Kainuma, K. Riahi, A. Thomson, K. Hibbard, G. C. Hurtt, T. Kram, V. Krey, J.-F. Lamarque *et al.*, "The representative concentration pathways: an overview," *Climatic change*, vol. 109, pp. 5–31, 2011.

[24] W. Lutz, W. C. Sanderson, and S. Scherbov, *The End of World Population Growth in the 21st Century: New Challenges for Human Capital Formation and Sustainable Development*. London: Earthscan, April 2004.

[25] J. J. Alonso Fernández, J. E. Devesa Carpio, M. Devesa Carpio, I. Domínguez Fabián, B. Encinas Goenechea, and R. Meneu Gaya, "Towards an adequate and sustainable replacement rate in defined benefit pension systems: The case of spain," *International Social Security Review*, vol. 71, no. 1, pp. 51–70, 2018.

[26] R. K. Morgan, "Environmental impact assessment: the state of the art," *Impact Assessment and Project Appraisal*, vol. 30, no. 1, pp. 5–14, 2012.

[27] J. Rogelj, M. Schaeffer, P. Friedlingstein, N. P. Gillett, D. P. Van Vuuren, K. Riahi, M. Allen, and R. Knutti, "Differences between carbon budget estimates unravelled," *Nature Climate Change*, vol. 6, no. 3, pp. 245–252, 2016.

[28] A. S. Luccioni and A. Hernandez-Garcia, "Counting carbon: A survey of factors influencing the emissions of machine learning," 2023.

[29] P. Henderson, J. Hu, J. Romoff, E. Brunskill, D. Jurafsky, and J. Pineau, "Towards the systematic reporting of the energy and carbon footprints of machine learning," *J. Mach. Learn. Res.*, vol. 21, no. 1, jan 2020.

[30] L. Zhang, Y. Yan, W. Xu, J. Sun, Y. Zhang, and D. Gong, "Carbon emission calculation and influencing factor analysis based on industrial big data in the "double carbon" era," *Intell. Neuroscience*, vol. 2022, jan 2022.

[31] R. Munsif, M. Zubair, A. Aziz, and M. N. Zafar, "Industrial air emission pollution: potential sources and sustainable mitigation," in *Environmental Emissions*. IntechOpen, 2021.

[32] X. Qiu, T. Parcollet, D. J. Beutel, T. Topal, A. Mathur, and N. D. Lane, "Can federated learning save the planet?" in *NeurIPS-Tackling Climate Change with Machine Learning*, 2020.

[33] S. Savazzi, V. Rampa, S. Kianoush, and M. Bennis, "An energy and carbon footprint analysis of distributed and federated learning," *IEEE Transactions on Green Communications and Networking*, vol. 7, no. 1, pp. 248–264, 2022.

[34] X. Qiu, T. Parcollet, J. Fernández-Marqués, P. P. B. de Gusmão, D. J. Beutel, T. Topal, A. Mathur, and N. D. Lane, "A first look into the carbon footprint of federated learning," *CoRR*, vol. abs/2102.07627, 2021.

[35] M. Saifuzzaman, T. N. Ananna, M. J. M. Chowdhury, M. S. Ferdous, and F. Chowdhury, "A systematic literature review on wearable health data publishing under differential privacy," *International Journal of Information Security*, vol. 21, no. 4, pp. 847–872, 2022.

[36] R. Naidu, H. Diddee, A. Mulay, A. Vardhan, K. Ramesh, and A. Zamzam, "Towards quantifying the carbon emissions of differentially private machine learning," 2021.

[37] R. Nana, C. Tadonki, P. Dokládal, and Y. Mesri, "Energy concerns with hpc systems and applications," *arXiv preprint arXiv:2309.08615*, 2023.

[38] D. A. Patterson, J. Gonzalez, U. Holzle, Q. V. Le, C. Liang, L.-M. Munguía, D. Rothchild, D. R. So, M. Texier, and J. Dean, "The carbon footprint of machine learning training will plateau, then shrink," *Computer*, vol. 55, pp. 18–28, 2022.

[39] O. Shaikh, J. Saad-Falcon, A. P. Wright, N. Das, S. Freitas, O. I. Asensio, and D. H. Chau, "Energyvis: Interactively tracking and exploring energy consumption for ml models," 2021.

[40] P. Bakhtiarifard, C. Igel, and R. Selvan, "Ec-nas: Energy consumption aware tabular benchmarks for neural architecture search," in *ICASSP*

This article has been accepted for publication in IEEE Transactions on Sustainable Computing. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TSUSC.2025.3578834

2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, Apr. 2024.

[41] E. Strubell, A. Ganesh, and A. McCallum, "Energy and policy considerations for deep learning in nlp," 2019.

[42] N. Bannour, S. Ghannay, A. Névéol, and 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.

[43] D. Hershcovich, N. Webersinke, M. Kraus, J. A. Bingler, and M. Leippold, "Towards climate awareness in nlp research," *arXiv preprint arXiv:2205.05071*, 2022.

[44] A. Luccioni, S. Viguier, and A.-L. Ligozat, "Estimating the carbon footprint of bloom, a 176b parameter language model," *J. Mach. Learn. Res.*, vol. 24, pp. 253:1–253:15, 2022.

[45] H. Peng, Q. Cao, J. Dodge, M. E. Peters, J. Fernandez, T. Sherborne, K. Lo, S. Skjonsberg, E. Strubell, D. Plessas, I. Beltagy, E. P. Walsh, N. A. Smith, and H. Hajishirzi, "Efficiency pentathlon: A standardized arena for efficiency evaluation," 2023.

[46] Q. Cao, Y. K. Lal, H. Trivedi, A. Balasubramanian, and N. Balasubramanian, "Irene: Interpretable energy prediction for transformers," 2021.

[47] I. Lakim, E. Almazrouei, I. Abualhaol, M. Debbah, and J. Launay, "A holistic assessment of the carbon footprint of noor, a very large Arabic language model," in *Proceedings of BigScience Episode #5 – Workshop on Challenges & Perspectives in Creating Large Language Models*, A. Fan, S. Ilic, T. Wolf, and M. Gallé, Eds. virtual+Dublin: Association for Computational Linguistics, May 2022, pp. 84–94.

[48] A. Faiz, S. Kaneda, R. Wang, R. Osi, P. Sharma, F. Chen, and L. Jiang, "Llmcarbon: Modeling the end-to-end carbon footprint of large language models," *arXiv preprint arXiv:2309.14393*, 2023.

[49] S. M. Xie, H. Pham, X. Dong, N. Du, H. Liu, Y. Lu, P. S. Liang, Q. V. Le, T. Ma, and A. W. Yu, "Doremi: Optimizing data mixtures speeds up language model pretraining," *Advances in Neural Information Processing Systems*, vol. 36, 2024.

[50] X. Wang, C. Na, E. Strubell, S. Friedler, and S. Luccioni, "Energy and carbon considerations of fine-tuning bert," *arXiv preprint arXiv:2311.10267*, 2023.

[51] S. A. Khowaja, P. Khuwaja, K. Dev, W. Wang, and L. Nkenyereye, "Chatgpt needs spade (sustainability, privacy, digital divide, and ethics) evaluation: A review," *Cognitive Computation*, pp. 1–23, 2024.

[52] M. Shi, K. Currier, Z. Liu, K. Janowicz, N. Wiedemann, J. Verstegen, G. McKenzie, A. Graser, R. Zhu, and G. Mai, "Thinking geographically about ai sustainability," *AGILE: GIScience Series*, vol. 4, p. 42, 2023.

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

[54] N. Bannour, S. Ghannay, A. Névéol, and 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*, N. S. Moosavi, I. Gurevych, A. Fan, T. Wolf, Y. Hou, A. Marasović, and S. Ravi, Eds. Virtual: Association for Computational Linguistics, Nov. 2021, pp. 11–21.

[55] A. A. Chien, L. Lin, H. Nguyen, V. Rao, T. Sharma, and R. Wijayawardana, "Reducing the carbon impact of generative ai inference (today and in 2035)," in *Proceedings of the 2nd workshop on sustainable computer systems*, 2023, pp. 1–7.

[56] S. Kumar and R. Buyya, "Green cloud computing and environmental sustainability," *Harnessing green IT: principles and practices*, pp. 315–339, 2012.

[57] P. Jaquart, S. Köpke, and C. Weinhardt, "Machine learning for cryptocurrency market prediction and trading," *The Journal of Finance and Data Science*, vol. 8, pp. 331–352, 2022.

[58] M. Taddeo, A. Tsamados, J. Cowls, and L. Floridi, "Artificial intelligence and the climate emergency: Opportunities, challenges, and recommendations," *One Earth*, vol. 4, no. 6, pp. 776–779, 2021.

[59] O. Fadeyi, O. Krejcar, P. Maresova, K. Kuca, P. Brida, and A. Selamat, "Opinions on sustainability of smart cities in the context of energy challenges posed by cryptocurrency mining," *Sustainability*, vol. 12, no. 1, 2020.

[60] T. C. C. F. Project, "Cloud Carbon Footprint," https://github.com/cloud-carbon-footprint/cloudcarbon-footprint, Year Accessed.

[61] F. A. V. Gómez, "Tracarbon," https://github.com/fvaleye/tracarbon, Year Accessed.

[62] L. Lannelongue, J. Grealey, and M. Inouye, "Green algorithms: quantifying the carbon footprint of computation," *Advanced science*, vol. 8, no. 12, p. 2100707, 2021.

[63] "Green Algorithms," https://github.com/GreenAlgorithms/green-algorithms-tool.

[64] S. A. Budennyy, V. D. Lazarev, N. N. Zakharenko, A. N. Korovin, O. Plosskaya, D. V. Dimitrov, V. Akhripkin, I. Pavlov, I. V. Oseledets, I. S. Barsola *et al.*, "Eco2ai: carbon emissions tracking of machine learning models as the first step towards sustainable ai," in *Doklady Mathematics*, vol. 106, no. Suppl 1. Springer, 2022, pp. S118–S128.

[65] A. Lacoste, A. Luccioni, V. Schmidt, and T. Dandres, "Quantifying the carbon emissions of machine learning," 2019.

[66] L. F. W. Anthony, B. Kanding, and R. Selvan, "Carbontracker: Tracking and predicting the carbon footprint of training deep learning models," 2020.

[67] O. Shaikh, J. Saad-Falcon, A. P. Wright, N. Das, S. Freitas, O. Asensio, and D. H. Chau, "Energyvis: Interactively tracking and exploring energy consumption for ml models," in *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, ser. CHI EA '21. New York, NY, USA: Association for Computing Machinery, 2021.

[68] V. Schmidt, K. Goyal, A. Joshi, B. Feld, L. Conell, N. Laskaris, D. Blank, J. Wilson, S. Friedler, and S. Luccioni, "Codecarbon: estimate and track carbon emissions from machine learning computing," *Cited on*, vol. 20, 2021.

[69] M. Yusuf, P. Surana, G. Gupta, and K. Ramesh, "Curb your carbon emissions: Benchmarking carbon emissions in machine translation," 2022.

[70] M. AlShafeey and O. Rashdan, "Quantifying the impact of energy consumption sources on ghg emissions in major economies: A machine learning approach," *Energy Strategy Reviews*, vol. 49, p. 101159, 2023.

[71] U. Shahzad, T. Sengupta, A. Rao *et al.*, "Forecasting carbon emissions future prices using the machine learning methods," *Annals of Operations Research*, 2023.

[72] M. Rao, "Machine learning in estimating co₂ emissions from electricity generation," in *Engineering Problems*, M. S. Tsuzuki, R. Y. Takimoto, A. K. Sato, T. Saka, A. Barari, R. O. A. Rahman, and Y.-T. Hung, Eds. Rijeka: IntechOpen, 2021, ch. 13.

[73] I. D'Adamo, G. Ioppolo, Y. Shen, and M. A. Rosen, "Sustainability survey: Promoting solutions to real-world problems," *Sustainability*, vol. 14, no. 19, 2022.

[74] M. Yunus, *A world of three zeros: the new economics of zero poverty, zero unemployment, and zero net carbon emissions*. Hachette UK, 2017.

[75] G. E. Metcalf and J. H. Stock, "Integrated assessment models and the social cost of carbon: A review and assessment of u.s. experience," *Review of Environmental Economics and Policy*, vol. 11, no. 1, pp. 80–99, 2017.

[76] W. Nordhaus, "Chapter 16 - integrated economic and climate modeling," in *Handbook of Computable General Equilibrium Modeling SET, Vols. 1A and 1B*, ser. Handbook of Computable General Equilibrium Modeling, P. B. Dixon and D. W. Jorgenson, Eds. Elsevier, 2013, vol. 1, pp. 1069–1131.

[77] C. Griffiths, E. Kopits, A. Marten, C. Moore, S. Newbold, and A. Wolverton, *Chapter 4. The Social Cost of Carbon: Valuing Carbon Reductions in Policy Analysis**. USA: International Monetary Fund, 2012, p. ch04.

[78] B. Acun, B. Lee, F. Kazhamiaka, K. Maeng, U. Gupta, M. Chakkaravarthy, D. Brooks, and C.-J. Wu, "Carbon explorer: A holistic framework for designing carbon aware datacenters," in *Proceedings of the 28th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2*, ser. ASPLOS 2023. New York, NY, USA: Association for Computing Machinery, 2023, p. 118–132.

[79] S. Naumann, M. Dick, E. Kern, and T. Johann, "The greensoft model: A reference model for green and sustainable software and its engineering," *Sustainable Computing: Informatics and Systems*, vol. 1, no. 4, pp. 294–304, 2011.

[80] U. Gupta, M. Elgamal, G. Hills, G.-Y. Wei, H.-H. S. Lee, D. Brooks, and C.-J. Wu, "Act: Designing sustainable computer systems with an architectural carbon modeling tool," in *Proceedings of the 49th Annual International Symposium on Computer Architecture*, 2022, pp. 784–799.

[81] J. Dodge, T. Prewitt, R. Tachet des Combes, E. Odmark, R. Schwartz, E. Strubell, A. S. Luccioni, N. A. Smith, N. DeCario, and W. Buchanan, "Measuring the carbon intensity of ai in cloud instances," in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 2022, pp. 1877–1894.

[82] M. Mohsin, A. Rasheed, H. Sun, J. Zhang, R. Iram, N. Iqbal, and Q. Abbas, "Developing low carbon economies: an aggregated composite index based on carbon emissions," *Sustainable Energy Technologies and Assessments*, vol. 35, pp. 365–374, 2019.

[83] F. Rohde, J. Wagner, A. Meyer, P. Reinhard, M. Voss, U. Petschow, and A. Mollen, "Broadening the perspective for sustainable ai: Comprehensive sustainability criteria and indicators for ai systems," 2023.

[84] K. Lottick, S. Susai, S. A. Friedler, and J. P. Wilson, "Energy usage reports: Environmental awareness as part of algorithmic accountability," 2019.

[85] T. Trébaol, "Cumulator — a tool to quantify and report the carbon footprint of machine learning computations and communication in academia and healthcare," 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:235654375

[86] M. T. Trebaol, M.-A. Hartley, and H. S. Ghadikolaei, "A tool to quantify and report the carbon footprint of machine learning computations and communication in academia and healthcare," *Infoscience EPFL: record*, vol. 278189, p. 27, 2020.

[87] C. F. Rodrigues, G. Riley, and M. Luján, "Synergy: An energy measurement and prediction framework for convolutional neural networks on jetson tx1," in *Proceedings of the international conference on parallel and distributed processing techniques and applications (PDPTA)*. The Steering Committee of The World Congress in Computer Science, Computer . . . , 2018, pp. 375–382.

[88] A. Parashar, P. Raina, Y. S. Shao, Y.-H. Chen, V. A. Ying, A. Mukkara, R. Venkatesan, B. Khailany, S. W. Keckler, and J. Emer, "Timeloop: A systematic approach to dnn accelerator evaluation," in *2019 IEEE international symposium on performance analysis of systems and software (ISPASS)*. IEEE, 2019, pp. 304–315.

[89] Y. N. Wu, J. S. Emer, and V. Sze, "Accelergy: An architecture-level energy estimation methodology for accelerator designs," in *2019 IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*. IEEE, 2019, pp. 1–8.

[90] D. Wright, C. Igel, G. Samuel, and R. Selvan, "Efficiency is not enough: A critical perspective of environmentally sustainable ai," 2023.

[91] M. Khalooei, M. Mehdi Homayounpour, and M. Amirmazlaghani, "Layer-wise regularized adversarial training using layers sustainability analysis framework," *Neurocomputing*, vol. 540, p. 126182, 2023.

[92] S. M. Hasan, A. R. Shahid, and A. Imteaj, "Towards sustainable secureml: Quantifying carbon footprint of adversarial machine learning," in *2024 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 2024, pp. 1359–1364.

[93] S. M. Hasan, A. R. Shahid, and A. Imteaj, "Evaluating sustainability and social costs of adversarial training in machine learning," *IEEE Consumer Electronics Magazine*, vol. 14, no. 3, pp. 27–34, 2025.

[94] M. K. Dixit, C. H. Culp, and J. L. Fernandez-Solis, "Calculating primary energy and carbon emission factors for the united states' energy sectors," *RSC Advances*, vol. 4, no. 97, pp. 54 200–54 216, 2014.

[95] I. Dincer, "Renewable energy and sustainable development: a crucial review," *Renewable and sustainable energy reviews*, vol. 4, no. 2, pp. 157–175, 2000.

[96] S. Borozan, S. Giannelos, P. Falugi, A. Moreira, and G. Strbac, "Machine learning-enhanced benders decomposition approach for the multi-stage stochastic transmission expansion planning problem," *Electric Power Systems Research*, vol. 237, p. 110985, 2024.

[97] S. Bharany, S. Sharma, O. I. Khalaf, G. M. Abdulsahib, A. S. Al Humaimeedy, T. H. H. Aldhyani, M. Maashi, and H. Alkahtani, "A systematic survey on energy-efficient techniques in sustainable cloud computing," *Sustainability*, vol. 14, no. 10, 2022.

[98] A. K. Feroz, H. Zo, and A. Chiravuri, "Digital transformation and environmental sustainability: A review and research agenda," *Sustainability*, vol. 13, no. 3, 2021.

[99] T. Alam, "Cloud computing and its role in the information technology," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 1, no. 2, pp. 108–115, April 2020.

[100] Z. Yao, Y. Lum, A. Johnston, L. M. Mejia-Mendoza, X. Zhou, Y. Wen, A. Aspuru-Guzik, E. H. Sargent, and Z. W. Seh, "Machine learning for a sustainable energy future," 2022.

[101] I. Kim, B. Kim, and D. Sidorov, "Machine learning for energy systems optimization," p. 4116, 2022.

[102] S. Giannelos, S. Borozan, G. Strbac, T. Zhang, and W. Kong, "Vehicle-to-grid: quantification of its contribution to security of supply through the f-factor methodology," *Sustainable Energy Research*, vol. 11, no. 1, p. 32, 2024.

[103] I. Konstantelos, S. Giannelos, and G. Strbac, "Strategic valuation of smart grid technology options in distribution networks," *IEEE Transactions on Power Systems*, vol. 32, no. 2, pp. 1293–1303, 2016.

[104] H. Scells, S. Zhuang, and G. Zuccon, "Reduce, reuse, recycle: Green information retrieval research," in *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2022, pp. 2825–2837.

[105] A. Bose and S. Nag, "Green computing – a survey of the current technologies," *Asia-Pacific Journal of Management and Technology*, vol. 03, pp. 01–15, 10 2022.

[106] B. Saha, "Green computing," *International Journal of Computer Trends and Technology (IJCTT)*, vol. 14, no. 2, pp. 46–50, 2014.

[107] T. Choudhary, V. Mishra, A. Goswami, and J. Sarangapani, "A comprehensive survey on model compression and acceleration," *Artificial Intelligence Review*, vol. 53, pp. 5113–5155, 2020.

[108] M. Zhu and S. Gupta, "To prune, or not to prune: exploring the efficacy of pruning for model compression," *arXiv preprint arXiv:1710.01878*, 2017.

[109] O. Spantidi and I. Anagnostopoulos, "Automated energy-efficient dnn compression under fine-grain accuracy constraints," in *2023 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, 2023, pp. 1–6.

[110] S. M. Hasan, A. R. Shahid, and A. Imteaj, "The environmental price of intelligence: Evaluating the social cost of carbon in machine learning," in *2024 IEEE Conference on Technologies for Sustainability (SusTech)*, 2024, pp. 397–403.

[111] S. Pei, J. Luo, S. Liang, H. Ding, X. Ye, and M. Chen, "Carbon emissions reduction of neural network by discrete rank pruning," *CCF Transactions on High Performance Computing*, vol. 5, no. 3, pp. 334–346, 2023.

[112] W. Jooste, R. Haque, and A. Way, "Knowledge distillation: A method for making neural machine translation more efficient," *Inf.*, vol. 13, p. 88, 2022.

[113] G. Moro, L. Ragazzi, and L. Valgimigli, "Carburacy: summarization models tuning and comparison in eco-sustainable regimes with a novel carbon-aware accuracy," in *Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence and Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence and Thirteenth Symposium on Educational Advances in Artificial Intelligence*, ser. AAAI'23/IAAI'23/EAAI'23. AAAI Press, 2023.

[114] E. Memmel, C. Menzen, J. Schuurmans, F. Wesel, and K. Batselier, "Position: Tensor networks are a valuable asset for green ai," *arXiv preprint arXiv:2205.12961*, 2022.

[115] X. He, K. Zhao, and X. Chu, "Automl: A survey of the state-of-the-art," *Knowledge-Based Systems*, vol. 212, p. 106622, 2021.

[116] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *Journal of Big data*, vol. 3, pp. 1–40, 2016.

[117] R. Al-Hajj, A. Assi, B. Neji, R. Ghandour, and Z. Al Barakeh, "Transfer learning for renewable energy systems: A survey," *Sustainability*, vol. 15, no. 11, 2023.

[118] Z. Dong, X. Zhang, L. Zhang, S. Giannelos, and G. Strbac, "Flexibility enhancement of urban energy systems through coordinated space heating aggregation of numerous buildings," *Applied Energy*, vol. 374, p. 123971, 2024.

[119] N. Milojevic-Dupont and F. Creutzig, "Machine learning for geographically differentiated climate change mitigation in urban areas," *Sustainable Cities and Society*, vol. 64, p. 102526, 2021.

[120] X. Lu, K. Ota, M. Dong, C. Yu, and H. Jin, "Predicting transportation carbon emission with urban big data," *IEEE Transactions on Sustainable Computing*, vol. 2, no. 4, pp. 333–344, 2017.

[121] Bitir-Istrate, Ioan, Gheorghiu, Cristian, and Gheorghiu, Miruna, "The transition towards an environmental sustainability for cryptocurrency mining," *E3S Web Conf.*, vol. 294, p. 03004, 2021.

[122] H. Obracht-Prondzyńska, E. Duda, H. Anacka, and J. Kowal, "Greencoin as an ai-based solution shaping climate awareness," *International Journal of Environmental Research and Public Health*, vol. 19, no. 18, p. 11183, 2022.

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[123] P. Kopelias, E. Demiridi, K. Vogiatzis, A. Skabardonis, and V. Zafiropoulou, "Connected & autonomous vehicles–environmental impacts–a review," *Science of the total environment*, vol. 712, p. 135237, 2020.

[124] R. Reinhardt, I. Christodoulou, S. Gassó-Domingo, and B. A. García, "Towards sustainable business models for electric vehicle battery second use: A critical review," *Journal of environmental management*, vol. 245, pp. 432–446, 2019.

[125] T. Islam, M. A. Sheakh, A. N. Jui, O. Sharif, and M. Z. Hasan, "A review of cyber attacks on sensors and perception systems in autonomous vehicle," *Journal of Economy and Technology*, 2024.

[126] R. R. Kumar and K. Alok, "Adoption of electric vehicle: A literature review and prospects for sustainability," *Journal of Cleaner Production*, vol. 253, p. 119911, 2020.

[127] W. Pedrycz, "Towards green machine learning: challenges, opportunities, and developments," *Journal of Smart Environments and Green Computing*, vol. 2, no. 4, pp. 163–174, 2022.

[128] R. Arshad, S. Zahoor, M. A. Shah, A. Wahid, and H. Yu, "Green iot: An investigation on energy saving practices for 2020 and beyond," *IEEE Access*, vol. 5, pp. 15 667–15 681, 2017.

[129] D. Trihinas, L. Thamsen, J. Beilharz, and M. Symeonides, "Towards energy consumption and carbon footprint testing for ai-driven iot services," in *2022 IEEE International Conference on Cloud Engineering (IC2E)*. IEEE, 2022, pp. 29–35.

[130] M. A. Albreem, A. M. Sheikh, M. H. Alsharif, M. Jusoh, and M. N. M. Yasin, "Green internet of things (giot): Applications, practices, awareness, and challenges," *IEEE Access*, vol. 9, pp. 38 833–38 858, 2021.

[131] M. A. Albreem, A. A. El-Saleh, M. Isa, W. Salah, M. Jusoh, M. Azizan, and A. Ali, "Green internet of things (iot): An overview," in *2017 IEEE 4th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA)*. IEEE, 2017, pp. 1–6.

[132] P. Rajkumar, "Gauging carbon footprint of ai/ml implementations in smart cities: Methods and challenges," in *2022 Seventh International Conference on Fog and Mobile Edge Computing (FMEC)*. IEEE, 2022, pp. 1–5.

[133] N. Sharma and D. Panwar, "Green iot: Advancements and sustainability with environment by 2050," in *2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 2020, pp. 1127–1132.

[134] I. Sittón-Candanedo, R. S. Alonso, Ó. García, L. Muñoz, and S. Rodríguez-González, "Edge computing, iot and social computing in smart energy scenarios," *Sensors*, vol. 19, no. 15, p. 3353, 2019.

[135] R. Verdecchia, J. Sallou, and L. Cruz, "A systematic review of green ai," 2023.

[136] J. Andersen, A. Mancini, M. Bosetti, P. Solovyev, T. Nardin, R. Larcher, E. Franciosi *et al.*, "Enrichment of model-cheeses with blackcurrant or cornelian cherry increases the total amount of polyphenols," in *36th EFFoST International conference: shaping the production of sustainable, healthy foods for the future, Dublin, Ireland, 7-9 November 2022*. IE, 2022, p. 522.

[137] R. Schwartz, J. Dodge, N. A. Smith, and O. Etzioni, "Green ai," 2019.

[138] R. Verdecchia, J. Sallou, and L. Cruz, "A systematic review of green ai," 2023.

[139] J. Xu, W. Zhou, Z. Fu, H. Zhou, and L. Li, "A survey on green deep learning," 2021.

[140] A. Yousefpour, S. Guo, A. Shenoy, S. Ghosh, P. Stock, K. Maeng, S.-W. Krüger, M. Rabbat, C.-J. Wu, and I. Mironov, "Green federated learning," 2023.

[141] A. Abbasi, F. Dong, X. Wang, H. Leung, J. Zhou, and S. Drew, "Fedgreen: Carbon-aware federated learning with model size adaptation," 2024.

[142] B. Guler and A. Yener, "Sustainable federated learning," 2021.

[143] S. Savazzi, S. Kianoush, V. Rampa, and M. Bennis, "A framework for energy and carbon footprint analysis of distributed and federated edge learning," in *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. IEEE, 2021, pp. 1564–1569.

[144] A. Clemm and C. Westphal, "Challenges and opportunities in green networking," in *2022 IEEE 8th International Conference on Network Softwarization (NetSoft)*. IEEE, 2022, pp. 43–48.

[145] G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter, "Continual lifelong learning with neural networks: A review," *Neural Networks*, vol. 113, pp. 54–71, 2019.

[146] C. R. Corrado, S. M. DeLong, E. G. Holt, E. Y. Hua, and A. Tolk, "Combining green metrics and digital twins for sustainability planning and governance of smart buildings and cities," *Sustainability*, vol. 14, no. 20, 2022.

[147] K. Siau and W. Wang, "Artificial intelligence (ai) ethics: Ethics of ai and ethical ai," *Journal of Database Management*, vol. 31, pp. 74–87, 03 2020.

[148] G. Tamburrini, "The ai carbon footprint and responsibilities of ai scientists," *Philosophies*, vol. 7, no. 1, p. 4, 2022.

[149] Y. Nakao, L. Strappelli, S. Stumpf, A. Naseer, D. Regoli, and G. D. Gamba, "Towards responsible ai: A design space exploration of human-centered artificial intelligence user interfaces to investigate fairness," 2022.

[150] T. Yoo, H. Lee, S. Oh, H. Kwon, and H. Jung, "Visualizing the carbon intensity of machine learning inference for image analysis on tensorflow hub," in *Companion Publication of the 2023 Conference on Computer Supported Cooperative Work and Social Computing*, 2023, pp. 206–211.

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