SUSTAINABLE AI: STRATEGIES TO REDUCE THE ENVIRONMENTAL FOOTPRINTS OF AI

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Original Article

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Abstract

As the demand for artificial intelligence is increasing in modern technology, the emergence of AI in sectors like healthcare, finance, retail and e-commerce, manufacturing, transportation, education, agriculture, energy, law and legal services, entertainment and media, government and public services have been available since recent decades. Despite AI's extensive impact on these sectors, the environmental impact, primarily through energy consumption and carbon footprints, is the major sustainability issue. The increasing computational requirements for the AI models put a strain on the energy resources, making AI sustainability a vital challenge. The author looks into energy-efficient algorithms, sustainable hardware, and the role of green data centres in supporting AI sustainability. The author also discuss how emerging technologies like quantum computing could improve the energy efficiency of AI systems. By reviewing case studies, such as AI-based optimizations in data centres and machine learning models for energy savings, the author highlights successful examples of AI sustainability. Our findings show that adding sustainable practices to AI development can lower its environmental impact while keeping its performance. This paper highlights the importance of teamwork among researchers, industries, and policymakers to create a more sustainable AI ecosystem for the future.

Keywords: Environmental Footprint; Eco-Friendly AI Strategies; Green Technology; Sustainable AI; Sustainable Development

Introduction

Artificial Intelligence (AI) has become a key part of technology development, impacting many industries and applications. It is changing how the author lives, works, and interacts in areas like healthcare, finance, retail, agriculture, energy, and law enforcement. The quick growth of AI technologies, driven by improvements in machine learning, deep learning, and natural language processing, has created new opportunities and efficiencies across different sectors. However, as more people adopt AI, its environmental impact is also rising, becoming a major concern with climate change and sustainability issues. AI models, especially large-scale deep learning algorithms, need a lot of computational power for training and use. The demand for vast amounts of data and the processing power to manage these datasets leads to high energy consumption. Data centres, which are essential for AI infrastructure, also consume a lot of electricity, most of which still comes from non-renewable sources. This increasing energy demand has resulted in higher carbon emissions, making AI's environmental impact even worse. In addition to the energy used to run AI models, the production and disposal of hardware, like GPUs, TPUs, and other specialised chips, also harm the environment. The life cycle of these components, from making them to disposing of them, can lead to serious ecological problems, including resource depletion and waste. Given the fast pace of AI innovation, the author needs to explore ways to lessen the

Received 29th July 2025; Revised 13th August 2025; Accepted 4th September 2025

environmental impact of these technologies. This paper will investigate different methods for making AI more sustainable, focusing on energy-efficient algorithms, eco-friendly hardware, and the importance of green data centres in reducing the energy use of AI systems. The author will also examine emerging technologies like quantum computing, which could greatly enhance the energy efficiency of AI models. By reviewing existing case studies and real-world applications, the author will highlight successful examples of AI sustainability and suggest ways to incorporate environmentally friendly practices into AI development. In the end, this paper aims to show that the author can lessen the environmental effects of AI without sacrificing its performance or potential.

Literature Review

The growing integration of Artificial Intelligence (AI) across sectors such as healthcare, finance, energy, and education has created new efficiencies but also raised concerns about its environmental impact [1]. The training and deployment of AI models—particularly deep learning systems—demand significant computational power and data processing capacity, which contribute to high energy consumption and increased carbon emissions [2]. This issue has led researchers to advocate for "Green AI", a paradigm focused on enhancing the sustainability of AI technologies while maintaining their performance [3].

A major source of AI's environmental footprint stems from data centres, which are estimated to consume nearly 2% of global electricity, a figure expected to rise as AI adoption accelerates [4]. Studies highlight the importance of green data centres employing renewable energy sources and energy-efficient cooling systems [5, 6]. For example, Google and Microsoft have implemented AI-driven optimisation centres that employ renewable energy integration in their data centre operations to minimise energy waste [7]. Such initiatives exemplify corporate responsibility towards achieving carbon neutrality in AI infrastructure.

Beyond data centres, the production and disposal of AI hardware—especially GPUs and TPUs—poses ecological risks through resource depletion and e-waste accumulation [8]. Sustainable hardware design using recyclable materials and extended device lifespans has therefore emerged as a crucial research area. Scholars such as Cvjetko Bubalo, Vidović, Radojčić Redovniković, and Jokić [9] have emphasised the potential of green solvents and eco-friendly materials in mitigating the environmental toll of technological manufacturing.

To curb computational energy use, algorithmic innovations have become central to sustainable AI. Techniques like model pruning, quantisation, and knowledge distillation reduce redundant parameters and computational overhead, leading to substantial energy savings [10]. Complementary methods such as transfer learning and federated learning have also proven effective in lowering training costs and energy requirements by reusing existing models and decentralising computation [8]. These strategies align with Wenninger et al. [11], who proposed a "sustainable machine learning balance sheet" to evaluate algorithmic efficiency in energy applications.

Emerging computing paradigms—including quantum and neuromorphic computing—hold promise for enhancing AI sustainability. Quantum systems process data through qubits, offering exponential improvements in computational speed and energy efficiency [12]. Similarly, neuromorphic chips mimic neural networks in the human brain, drastically reducing power consumption for AI inference and pattern recognition [7]. Although they are still under development, these technologies could revolutionise AI sustainability in the coming decade.

AI itself can be leveraged to improve sustainability across industries. Applications in smart grids, energy-efficient buildings, and precision agriculture demonstrate how AI can optimise energy distribution, reduce waste, and promote eco-friendly practices [13,14]. Thus, AI functions not only as a contributor to environmental stress but also as a potential enabler of ecological resilience.

Achieving sustainable AI requires a holistic approach, encompassing energy-efficient algorithms, green data centres, eco-conscious hardware, and next-generation computing systems [15]. As Van Wynsberghe [1] and Clemm et al. [3] emphasise, collaboration among researchers, policymakers, and industry stakeholders is essential to embedding sustainability principles within AI's design and governance. By integrating these multidimensional strategies, AI can transition from being an environmental burden to a driving force for global sustainability.

Discussion

Environmental Impacts of AI

The fast growth of Artificial Intelligence (AI) applications has changed many sectors significantly. These changes have made processes more efficient and easier to manage. However, with these improvements come important concerns about the environment. AI systems, especially those that use large machine learning models, rely heavily on a lot of computing power, which results in high energy use. As the need for more complex AI models and data processing rises, the environmental impact of these technologies has also grown [12]. Energy consumption and carbon emissions are the main environmental issues the author face.

Energy Consumption in AI Models

At the heart of AI's environmental impact is the huge energy needed to train, run, and scale AI models. The computing requirements for training deep learning models, for example, have increased significantly in recent years. These models often need to process large datasets and carry out extensive calculations over long periods, sometimes even days or weeks, depending on the dataset size and model complexity. The energy used for training AI models can vary greatly based on factors like the model type, the number of parameters, the size of the training dataset, and how long the training lasts. The energy consumed during AI model training raises concerns due to its direct link to the carbon emissions from electricity production. Training a single large model, like those used for natural language processing or image recognition, can use several kilowatt-hours (kWh) of electricity, often matching the energy consumption of an average household over weeks or even months. As AI models become more advanced and data-intensive, the energy required to train and maintain these systems keeps increasing, worsening their carbon footprint. If the energy for training and operating these models comes from fossil fuels, the environmental impact becomes even more serious, making energy consumption one of the biggest challenges for AI sustainability [1].

Carbon Footprint of Data Centres

The vast computational requirements for artificial intelligence systems are essentially met by data centres, which are the core units for processing, storage, and data management [2]. These data centres house the extremely powerful servers that are necessary to run AI models, and they are, in essence, very energy-consuming. The energy used to keep the servers working at all times, as well as the extra energy for cooling, can make up a substantial part of the total electricity consumption of a data centre. Data centres, according to some sources, are responsible for almost 2% of global electricity usage, and this number will increase with the growth of the AI and other data-intensive applications markets.

Hence, the carbon footprint of data centres is something that should cause a lot of concern, especially in cases where the electricity they provide comes from non-renewable sources, i.e., coal, natural gas, or oil. The environmental impact of AI systems is thus very high in areas where energy still largely comes from fossil fuels. Even though a certain number of companies have taken proactive measures and are using clean energy for their data centres, the industry as a whole still faces a hurdle in the transition to a sustainable energy model. As AI adoption grows, the demand for data centres will continue to increase, making it even more essential and effective to address the energy and environmental challenges of these centres by implementing energy-efficient measures and utilising clean energy.

Environmental Impact of AI Hardware

Beyond the energy consumed during AI operations, the environmental consequences of producing and disposing of AI hardware also play a crucial role in the overall sustainability of AI technologies. Specialised hardware, such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), are integral to the performance of AI systems. These components are designed to handle the complex calculations required by machine learning algorithms, but their production involves the extraction of rare earth metals and other resources, a process that can be highly resource-intensive.

The environmental impact of hardware production is compounded by the mining and processing of materials required for manufacturing these chips. This extraction process often leads to habitat destruction, water contamination, and soil degradation. Additionally, the energy required to manufacture these hardware components adds to the overall carbon footprint of AI systems [13]. As AI hardware advances, the demand for more efficient and powerful chips grows, further straining the planet's resources.

Equally concerning is the disposal of outdated or obsolete hardware. With the rapid pace of technological innovation, many AI-related components, such as GPUs and other processors, are quickly rendered obsolete, contributing to the growing issue of electronic waste (e-waste). Improper disposal of e-waste can result in toxic chemicals leaching into the environment, posing serious risks to both ecosystems and human health. To mitigate these environmental risks, it is essential to address the entire lifecycle of AI hardware, from resource extraction to manufacturing, usage, and disposal.

Energy-Efficient Algorithms

The increasing demand for AI applications has highlighted the importance of optimising computational efficiency to minimise energy consumption. Traditional AI models, particularly deep learning models, tend to be resource-intensive due to their complexity and the size of the datasets they process. As AI becomes more prevalent, it's crucial to develop algorithms that are not only accurate but also energy-efficient, to ensure that the environmental impact of AI is manageable. Energy-efficient algorithms are designed to reduce the computational resources required for training and inference, thereby lowering the overall energy consumption of AI systems.

Optimisation Techniques for Reducing Energy Use

One approach to creating energy-efficient AI models is through the optimisation of existing algorithms. Several techniques can be used to reduce the computational load and improve the efficiency of AI models without sacrificing their performance. These techniques include model pruning, quantisation, and knowledge distillation.

- **Model Pruning:** Model pruning is a process in which unnecessary or redundant parameters in a machine learning model are removed. By reducing the number of parameters, the model requires less computation and memory during both training and inference. This reduction in size leads to lower energy consumption, as fewer operations are required. Pruning can be applied to deep neural networks, which are known for their large number of parameters, making them especially resource-intensive.

- **Quantisation:** Quantisation is a technique used to reduce the precision of the numerical values used in AI computations. Typically, AI models operate using high-precision floating-point numbers, which require more computational power. Quantisation reduces the precision of these numbers, typically to fixed-point representations, which reduces the number of bits needed for calculations. These modifications can result in faster computations and reduced energy usage, especially in hardware with limited processing capabilities, such as edge devices.

- **Knowledge Distillation:** Knowledge distillation is a method in which a smaller, more efficient model (the "student") is trained to replicate the performance of a larger, more complex model (the "teacher"). The smaller model can then perform the same tasks with fewer computational resources, resulting in lower energy consumption. This technique has been particularly useful in deploying AI models to resource-constrained devices, where energy efficiency is critical.

Efficient Training Methods

Another critical area where energy consumption can be reduced is during the training process. Training large-scale AI models often requires enormous computational resources, leading to significant energy consumption. Several approaches have been developed to make the training process more energy-efficient.

- **Transfer Learning:** Transfer learning is a technique in which a pre-trained model, typically trained on a large dataset, is fine-tuned for a specific task. This approach reduces the need for training a model from scratch, which can be computationally expensive and energy-intensive. By leveraging pre-trained models, transfer learning can significantly cut down the amount of computational power required, saving both time and energy.

- **Federated Learning:** Federated learning is a decentralised approach to training AI models, where the data stays on the local devices and only model updates are shared with a central server. This method reduces the need to transfer large datasets to central servers, which helps save bandwidth and energy. Federated learning can be particularly useful in scenarios where large-scale data collection is impractical or when working with data that cannot leave local environments, such as in healthcare or finance.

- **Low-Rank Factorisation:** Low-rank factorisation involves approximating large matrices used in machine learning models with smaller, lower-rank matrices. This reduces the computational complexity of the model and the amount of memory required. Low-rank factorisation is particularly useful in large-scale deep learning models, where the weight matrices can become very large and resource-intensive.

Green AI and Algorithmic Efficiency

The term "Green AI" refers to the growing movement to make AI more sustainable by focusing on energy-efficient algorithms and reducing the carbon footprint of AI systems [3]. Researchers are increasingly aware of the environmental impact of training large AI models and are working to create algorithms that are both computationally efficient and environmentally friendly. By improving algorithmic efficiency, AI systems can deliver the same or even better performance while consuming fewer resources.

One key aspect of Green AI is designing algorithms that are well-suited for deployment on energy-efficient hardware, such as specialised chips or low-power devices. Green AI also emphasises the importance of conducting research into the energy costs associated with AI, encouraging transparency and awareness in the development of AI models [7].

Case Studies of Energy-efficient Algorithms

- **Google's TensorFlow Optimisations**
  Google's TensorFlow uses the XLA compiler to optimise machine learning models, reducing unnecessary computations and energy consumption during training and inference, making AI operations more efficient.

- **Facebook's AI for Data Centres**
  Facebook implements model pruning and quantisation algorithms to reduce the size of AI models, lowering energy use in data centres. Techniques like dynamic batching further improve energy efficiency without sacrificing performance.

- **Waymo's Autonomous Vehicle Algorithms**
  Waymo uses energy-efficient algorithms like lightweight CNNs and edge AI to reduce the computational load on autonomous vehicles, enabling real-time processing while minimising energy consumption.

Role of Green Data Centres in Supporting AI Sustainability

With the increasing demand for AI models, the energy consumption associated with running them in data centres has become a significant concern. Traditional data centres consume substantial amounts of electricity, which leads to high carbon emissions. Green data centres, designed with sustainability in mind, aim to address these challenges by integrating energy-efficient technologies and renewable energy sources.

- **Energy-Efficient Technologies in Green Data Centres**

  Green data centres prioritise the use of advanced cooling techniques, energy-efficient servers, and the integration of renewable energy sources, such as solar and wind. These technologies help reduce energy consumption, which is a crucial step towards making AI operations more sustainable. For instance, efficient cooling systems, like liquid cooling, significantly reduce the amount of energy required for temperature regulation in these centres.

- **Renewable Energy Integration**

  Green data centres actively seek to reduce their dependence on fossil fuels by using renewable energy sources. By incorporating solar panels, wind farms, or even hydropower, data centres can achieve carbon-neutral or even carbon-negative operations. This shift toward renewable energy is essential to reducing the environmental impact of AI technologies. Example: Google's Green Data Centres.

  Google's data centres are prime examples of energy-efficient infrastructure. The company has made significant strides towards using 100% renewable energy for its operations, including AI-driven optimisation of power and cooling systems. Google also leverages innovative cooling techniques, such as using the outside air to cool servers, thus minimising electricity consumption. Example: Microsoft's carbon-neutral data centres.

  Microsoft has committed to achieving carbon neutrality by 2030. As part of this commitment, the company has transitioned its data centres to renewable energy and integrated AI-based optimisation tools to reduce energy usage. In addition, Microsoft's use of AI systems ensures that the data centres operate at maximum efficiency, lowering energy consumption while handling AI workloads.

Emerging Technologies for AI Sustainability

The future of AI sustainability will heavily rely on the integration of emerging technologies that can further reduce energy consumption while enhancing performance. Among the most promising of these technologies are quantum computing and neuromorphic computing, both of which offer potential solutions for more efficient AI models and systems.

- **Quantum Computing and AI Sustainability**

  Quantum computing represents a leap in computing power and efficiency. Unlike classical computers, which process data in binary, quantum computers leverage quantum bits (qubits) that can exist in multiple states simultaneously. This capability enables quantum computers to process complex datasets far more efficiently than traditional systems. For AI, this capability could lead to much faster training of models, reducing the energy required for computation.

  Quantum algorithms, such as those for optimisation, machine learning, and cryptography, could significantly reduce the energy costs associated with AI modelling training. For example, quantum computers can perform certain calculations exponentially faster than classical computers, which would allow AI models to be trained in a fraction of the time and with much less energy consumption. However, the full potential of quantum computing is still being explored, and significant advancements are needed in both hardware and software to make it a viable solution for mainstream AI applications.

- **Neuromorphic Computing**
  Neuromorphic computing is another emerging technology that mimics the structure and function of the human brain. Neuromorphic chips, designed to process information in a way similar to how biological neurones and synapses work, are more energy-efficient than traditional processors. These chips are specifically designed for tasks like pattern recognition, sensory processing, and learning, which are fundamental to AI systems.

  The energy efficiency of neuromorphic computing comes from its ability to perform computations in a much more parallel and distributed manner than classical systems. Neuromorphic chips, by leveraging the brain's inherent efficiency in processing vast amounts of data with relatively low energy, have the potential to significantly reduce the energy consumption of AI systems. This makes them an exciting area of research for AI sustainability.

Role of AI in Energy Management and Sustainability
Interestingly, AI itself can play a significant role in addressing itsoptimise sustainability challenges. AI models can be used to optimise energy consumption in various sectors and contribute to sustainability efforts across industries.

- **AI for Smart Grids:** AI-powered smart grids use real-time data to optimise the generation, distribution, and consumption of electricity. These grids help reduce energy wastage by predicting demand and adjusting power distribution accordingly. AI optimisation can also integrate renewable energy sources more effectively by balancing the intermittent nature of wind and solar power with a constant demand for electricity.

- **AI for Energy-Efficient Buildings:** AI can optimise the energy usage of buildings by adjusting lighting, heating, and cooling systems based on real-time occupancy data and environmental conditions. Machine learning algorithms can predict energy needs and reduce waste, leading to more energy-efficient buildings and reduced environmental impact.

- **AI for Agriculture:** In agriculture, AI can help optimise the use of water, fertiliser, and other resources, significantly reducing the environmental impact of farming. AI-driven solutions like precision farming use real-time data to ensure that resources are used efficiently, minimising waste and improving crop yields.

Conclusion

AI technologies are rapidly advancing, and their potential for solving global challenges is immense. However, the environmental impact of these technologies cannot be ignored. As AI systems become more complex and data-intensive, their energy consumption and carbon footprint will only increase unless proactive steps are taken to address these issues.

Incorporating energy-efficient algorithms, sustainable hardware, green data centres, and emerging technologies like quantum and neuromorphic computing is essential to reducing the environmental impact of AI. Moreover, AI itself can be harnessed to optimize energy consumption across various industries, contributing to a more sustainable future.

The path forward requires collaboration between researchers, policymakers, and industry leaders to establish clear guidelines and standards for AI sustainability. As the AI ecosystem continues to grow, it is crucial to ensure that environmental considerations are prioritized alongside technological advancement.

To build a truly sustainable AI future, it is necessary to adopt a holistic approach that integrates energy efficiency into the design, development, and deployment of AI systems. With continued research and innovation, the environmental impact of AI can be mitigated, paving the way for AI-driven solutions that contribute to a more sustainable and equitable world.

Conflict of Interest
The authors declare that they have no conflict of interest.

Acknowledgement
The authors are thankful to the institutional authority for completion of the work.

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