Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2s (2026) | 330-335

Sustainable Artificial Intelligence: Balancing Performance, Energy Consumption, and Applications

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Peer Review Information

Type: *Article*
Received: *12 April 2026*
Revised: *03 May 2026*
Accepted: *10 June 2026*
Published: *05 July 2026*

Abstract

The last few years have seen AI advance at a frankly dizzying pace. We've gotten better medical diagnostics, smarter climate models, real-time language translation — the works. But here's the uncomfortable part nobody likes to talk about: the systems behind these breakthroughs are enormous, and enormous systems eat enormous amounts of electricity. That electricity, more often than not, still comes from fossil fuels. This paper looks at what people in the field are calling "green AI" — the idea that we can keep pushing the technology forward without quietly burning the planet in the process. We'll go over where all that energy actually goes during machine learning, and what developers can realistically do about it.

Keywords: Green AI; Sustainable Artificial Intelligence; Energy Consumption; Machine Learning; Carbon Footprint; Energy-Efficient Computing

How to Cite This Article

Sawant, A., Salgaonkar, S., Angre, R., & Mondal, D. (2026). Sustainable artificial intelligence: Balancing performance, energy consumption, and applications. *Multidisciplinary Journal of Research in Engineering and Technology, 13*(2s), 330–335.

Introduction

Artificial Intelligence has rapidly evolved into a foundational technology of the twenty-first century. It enables machines to learn from data, recognize patterns, make predictions, and automate complex tasks. AI systems are presently employed in speech recognition, recommendation systems, autonomous vehicles, medical diagnostics, fraud detection, and climate forecasting. These capabilities render AI valuable across nearly all sectors of society.

Despite these benefits, the growth of AI has introduced new environmental and economic concerns. Modern machine learning models are becoming larger and more complex. Many state-of-the-art models contain millions or even billions of parameters that require repeated training over massive datasets. This process demands advanced graphical processing units, cloud servers, and large data centers. Such infrastructure consumes substantial amounts of electricity and often relies on non-renewable energy sources. Consequently, the expansion of AI has increased its carbon footprint and raised questions about sustainability [1], [2].

Another issue is that many AI systems are designed primarily to maximize accuracy, while the computational cost is frequently neglected. In many cases, a modest improvement in accuracy entails significantly higher energy consumption. This imbalance has prompted researchers to pursue sustainable artificial intelligence, wherein efficiency, environmental impact, and accessibility are considered alongside performance [2], [3].

Background And Related Work

An increasing number of researchers are examining the interplay between artificial intelligence (AI) and sustainability, specifically looking at how AI supports the goal of sustainable development as well as the potential for AI to create obstacles to that goal.

The following sections provide a brief overview of existing literature on green AI, the evaluation framework for AI model performance, the environmental impacts of large-scale AI systems and examples of AI being used to meet sustainability goals.

The concept of green AI provides a broader evaluation framework than the traditional one that primarily focuses on model accuracy. A major reason for this is that an increase in model accuracy is often accompanied by an increase in the number of parameters the model requires, thus increasing the time taken to train the model, which ultimately translates to higher energy consumption. Green AI proposes that a broader evaluation framework should also include the time it takes to train a model, energy used to train a model, memory required by a model, and the cost of a model [3].

The third area of literature reviewed in support of the development of AI systems is focused on environmental impacts of large-scale AI systems. The amount of energy consumed in training a very large language modelling or computer-vision-based AI system has been estimated to be equal to the annual electricity consumption of a large number of households, which has resulted in greater interest in tools for measuring energy consumption and increasing the standards for transparency in the reporting of energy consumption [2], [4].

Additionally, researchers have found that AI has significant potential to help achieve sustainability goals, such as increasing the efficiency and reliability of renewable energy supply forecasting, managing smart grids, optimizing traffic flow, managing waste, monitoring crop health, predicting disease outbreaks in plants and animals, and improving environmental health systems [1]. Because of the significant energy consumption of the vast majority of current AI systems, it is evident that AI is both a part of the problem and a part of the solution.

Finally, according to current academic literature, sustainability in AI comprises more than just sustainability with respect to energy [2]

Energy Consumption in Machine Learning

The energy use of machine learning (ML) systems starts from data collection and preprocessing. Raw datasets generally need to be cleaned, labelled, filtered and normalised prior to use as training datasets, which require significant data storage and processing throughout the preprocessing stage, particularly for large datasets.

Training the model (i.e., the process of training ML algorithms) is the most energy-intensive stage within the entire ML lifecycle. During the training process, the ML algorithms repeatedly change their internal parameters (the weights) in order to reduce the training time required for the modelling exercise. A deep learning model may need to change its parameters thousands of times over a number of training epochs. Furthermore, as ML models are trained on graphical processing units (GPUs) or used across multiple distributed clusters, the demand for electricity will be even greater [2].

Another additional stage where energy is consumed during ML system development is the hyperparameter optimisation (the tuning of the hyperparameters employed by the ML models) process. This process involves testing many combinations of the learning rate, batch size, model depth and model regularisation, which improves the quality of the models and results in the need for multiple repetitions (sometimes dozens and hundreds of times) of the training process.

Once the ML models have been deployed, they will continue to make predictions from that point in time. The energy used for building ML systems includes all the processing of prediction requests, typically on a real-time basis. Thus, many AI systems (i.e., recommendation engines, search engines, voice agents, autonomous devices, etc.) are required to provide real-time predictions for millions of users every day. Even though the energy consumed by each individual prediction can be relatively small, that sum of total energy consumed across millions of daily predictions from millions of total requests may consume a huge amount of energy [1],[6].

AI systems typically use hidden costs associated with storage (databases and model repositories) or when communicating (networking) with their users.

Ecofriendly Artificial Intelligence

Eco-Friendly AI is a type of AI that seeks to decrease the environmental impact of AI while still maintaining an adequate level of functionality. Instead of only using the most accurate model as a measurement of success, Eco-Friendly AI also looks at practical, efficient, and responsible solutions.

A branch of Eco-Friendly AI working on making AI itself sustainable will work on shortening training periods, compressing models, building more energy-efficient architectures, and reducing the amount of energy used by AI during inference, with the goal of creating systems that use less energy while maintaining their reliability [5].

Another branch will be to use AI to solve societal and environmental challenges; for example:

- Use of AI to optimize the operation of power grids
- Prediction of local weather patterns
- Improved irrigation management for agricultural purposes
- Monitoring levels of pollution
- Detection of forest fires
- Management of transportation systems

Through these efforts, Eco-Friendly AI is directly contributing to the sustainable development of our planet [1].

Eco-Friendly AI will also have a positive impact on increasing accessibility. As long as only large organizations with significant computing resources can afford to train state-of-the-art AI models, then the majority of research and innovation will continue to be concentrated in the large companies that are able to afford to build the infrastructure. Conversely, by using Eco-Friendly AI techniques, universities, start-up companies, and smaller research organizations will have a greater ability to participate in the development of AI technology with modest computing resources.

Energy Efficient AI Strategies

Many different techniques exist that can be used to reduce the energy consumption of AI systems.

One technique involves pruning models by removing unnecessary weights and neurons after they have been trained [2],[3]. It is common for deep models to be over parameterized, and thus eliminating redundant connections will lower memory utilization and cost to compute.

Quantizing reduces the precision of numerical values, e.g. reducing 32-bit values to 8 bits (also reduces computing requirements, speeds up inferencing process on hardware capable of supporting this) [2], [5].

Knowledge distillation is a further technique that allows for transferring knowledge from a large model to a smaller student model. The smaller student models generally achieve great predictive performance but at significantly reduced resource requirements than the larger model (when training).

Transfer learning is an additional effective technique that can help reduce energy consumption when creating AI models [2]. Instead of training new AI models from scratch, using a previously trained model and modifying it for a different task can save a tremendous amount of time, energy and data.

Efficient architectures, such as MobileNet, EfficientNet and light-weight transformers are created to be used by low-resource environments (e.g. mobile devices, edge systems).

In addition to using energy efficient techniques when developing AI systems, following better coding practices will have a significant impact. Properly optimizing data processing pipelines, eliminating unnecessary repetitive experiments, and carefully scheduling workloads will all save a substantial amount of energy.

Machines And Data Center Sustainability

AI Hardware Choice and Its Impact on Performance - AI uses a variety of advanced hardware (GPUs, TPUs, custom accelerators) that can carry out a greater number of computations faster while also consuming less energy when compared to typical processors.[2],[5]

The Increasing Use of Edge Computing - Due to the fact that edge computing allows data to be processed near its point of origin rather than having to move all data back and forth to remote cloud centers results in less network transportation, lower latency time, and a significant reduction in greenhouse gases as compared to sending everything out and back from remote facilities for processing.

Data Center Design/Operation - The sheer volume of servers (thousands) housed in large data centers by major AI players requires ongoing electricity input for both the purposes of processing and cooling. Using Sustainable best practices in data centers would include ensuring that superior cooling systems are provided, balancing workloads or processing demands on systems, using energy-efficient processors/chips, or executing renewable energy contracts.

Innovative Approaches for Data Center Sites (Colder Climates and Proximity to Wind/Solar Resources) - Many firms are site specific regarding building new data centers in either colder climates or proximity to renewable energy generation sources.[1],[4]

Lifespan-Wear and Tear - Since many devices must be replaced regularly (due to wear/tear or obsolescence), they create massive amounts of electronic waste, so Sustainable AI supports reuse, remanufacturing or recycling wherever feasible.

Energy Measurement & Evaluation

Accurate measurement is critical when it comes to maintaining sustainability. Without clear metrics to compare different systems and determine where waste is occurring, it’s nearly impossible to manage and reduce energy consumption and emissions effectively.

Researchers have developed many tools to help provide estimates for electricity consumption and carbon emissions. CodeCarbon, CarbonTracker, and sensor-based monitoring systems are a few examples of commonly used tools to understand a system's electricity usage and the carbon emissions associated with that usage [4]. These tools can measure processor utilization, runtime, memory usage, and the estimated local electricity intensity based on the overall consumption of each respective processor.

In addition to metrics that provide the total amount of energy consumed by a system, metrics exist to evaluate overall performance efficiency. For example, if model A has a slightly lower level of accuracy compared to model B, but model A uses significantly less energy during operation than model B; then model A may produce better results under actual deployment conditions.

The principles of sustainable AI should include the following information in a standardized way to ensure that researchers can fairly compare implementation systems, and develop AI responsibly: How long was the training period for the models; What type of hardware was used; What size data sets were utilized; What number of experiments were performed; What were the estimated emissions produced by all of the above metrics?

Measurement And Evaluation of Energy Consumption

The importance of accurate measurement in sustainability cannot be overstated. Without accurate metrics it is impossible to effectively manage your sustainability efforts, compare different systems of sustainability, or even identify practices that waste energy.

Using tools like CodeCarbon, CarbonTracker, and sensor-based monitoring systems, researchers can estimate the amount of electricity used and carbon emissions produced. These tools can measure processor utilization, runtime, memory usage, and the local electric intensity.

Beyond just raw energy value, new performance efficiency metrics will help you compare the accuracy of datasets with the amount of energy required to produce that dataset. A model that produces slightly less accurate results but requires substantially less amount of energy may be the better option when looking to be deployed.

To enable researchers to make sound and fair comparisons, transparent reporting should contain information such as total time spent training, type of hardware being used, size of the dataset, and number of experiments conducted. By ensuring these items are part of standard reporting, researchers will continue to develop their technologies responsibly and efficiently.

Sustainable AI Application

Sustainable AI has important applications across many industries.

For example:

Renewable Energy - AI can predict solar and wind generation, balance supply and demand, improve battery scheduling, and enable the integration of renewable energy into electric grids [4].

Agriculture - AI can support precision agriculture through providing early detection of crop diseases, soil monitoring, irrigation control, and crop yield prediction to minimize waste of water, fertilizers and pesticides.

Healthcare - Efficient AI models are used to support medical imaging, patient monitoring, and forecasting of disease outcomes by operating on portable devices.

Progress And Limitations

While there has been significant progress made in the last few years in this area, some issues remain unaddressed. For example, there is currently no single, globally accepted standard for the measurement of AI energy and carbon emissions. Tools can report varying amounts of these metrics depending on their underlying assumptions (including hardware) and model(s) used to calculate results.

Another limitation is the balance between accuracy and efficiency. In many important areas (for instance, medicine and safety), it may be difficult to reduce a model's size without also compromising its ability to produce reliable results.

In addition, access to sustainable computing hardware continues to be limited. The availability of energy-efficient accelerators and infrastructure that uses renewably generated energy is unevenly distributed throughout the world

Future research should focus on developing models that automatically optimize themselves by varying their level of complexity based on the difficulty level of the task; developing scheduling systems that are aware of carbon, developing hardware that can be recycled and improving the consistency of benchmarking standards across different platforms. Finally, policymakers could establish guidelines for sustainability for large-scale AI projects as they are developed.

It is equally important for developers who create AI applications to consider their environmental impact as part of the design process and not as an afterthought.

Conclusion

Artificial Intelligence (AI) brings many benefits, but it is also important to consider the environmental impact of AI. Machine learning has grown rapidly, which has increased demand for electric power, computer/data storage/processing power (i.e., for computer servers), and specialized computerized hardware for both machine learning and other applications. If the increased demand for energy and data continues unmanaged, it may be at odds with global sustainability goals.

AI is going to be one of the most consequential tools humanity builds in the twenty-first century. There's a real chance it helps us build a more sustainable civilization. But that future only works if the AI itself is built sustainably from the start. Bolting on green considerations after the fact, once the damage is already done, isn't going to cut it.

The next generation of AI should be judged not just on how smart it is, but on how fair, how efficient, and how clean it is. Going green has to be part of the blueprint — not the cleanup crew.

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