International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 19s,2025
https://theaspd.com/index.php

# Green Algorithms For A Sustainable Future Reducing The Carbon Footprint Of AI And Big Data

**[1]Nikhil Kassetty, [2]Xin Tain, [3]Dr. Parin Somani, [4]Mcxin Tee**
[1]AI Innovation Strategist and Technology Consultant, ORCID:0009-0003-7540-3656, Atlanta, GA, USA
[2]Doctor of Education Program in Education, Shinawatra University, 15517310971@163.com, ORCID 0009-0004-7390-2723
[3]CEO, London Organsation of Skills Development (LOSD), UK
[4]Faculty of Business and Communications, INTI International University, 71800 Nilai, Malaysia. ORCID 0000-0001-7990-8377

***Abstract—*** *The compounding growth of Artificial Intelligence (AI) and Big Data analytics has caused an unequaled hunger of computing assets to emerge that has is causing a huge elevation in the utilization of energy and carbon emissions across the globe. Though all of these technologies have brought about revolutionary solutions to the various sectors, their impact on the environment is increasingly becoming a thing of concern. The paper addresses the concepts and application of green algorithms which are energy efficient computational algorithm and are less harmful on the environment. Through the lifecycle of AI models and big data processing pipelines, we can single out the sources of energy wastage that are critical, and the ways of enhancing sustainability. In comparison we will show through comparative analysis how the model architecture optimization, data center management and training practices can be made to reduce carbon emission in a significant way without affecting the performance. The findings support the necessity to consider the principle of sustainability as an essential feature of designing such AI and data-intensive systems in the future.*
***Keywords—*** *Green algorithms, sustainable computing, energy-efficient AI, carbon footprint, big data analytics, eco-friendly machine learning, computational sustainability, green AI, climate-aware computing, energy optimization.*

## I. INTRODUCTION

Under the conditions of digital transformation, Artificial Intelligence (AI) and Big Data became the key technologies that can promote innovation, efficiency, and growth in various spheres: healthcare and education, finance and transportation, and so on. Their capabilities to take in, store and train large datasets and build complex machine learning models has allowed decision-making, automating processes, and predictive analysis that were unprecedented. But they highly depend on another unnoticed and unnoticed price, the fast growing carbon emission of high-performance computing (HPC) systems, cloud infrastructure, and data center activities. With the increasing complexity and the growing size of AI models, and the booming data, the volume of energy needed to power the systems is becoming a significant cause of environmental concerns [15].

Large-scale deep learning models have been pointed out as demanding significant energy resources to train in recent literature. To train a single large language model (e.g., GPT or BERT) may, in particular, use hundreds of megawatt-hours of electricity and emit equivalent carbon dioxide to dozens of passenger vehicle life-spans. On the same note, stateful data processing frameworks such as Apache Hadoop or Spark processes consume very large scale computing clusters and hence use too much electricity particularly when used continuously or in an inefficient manner [4].

The cumulative environmental implications of the adoption of these technologies, as industries adopt them, are becoming high, and the design, development, and deployment of AI and big data systems should be reassessed, as well [16].

Although the green agenda has taken root in other industries, the computing and AI communities are yet to take radical measures to embrace sustainability in their industry. Although accuracy, speed, and scalability are the main performance considerations in AI development, energy efficiency and sustainability are seldom deemed vital during model training or data pipelines construction. Such a gap has created a concept of so-called green algorithms, which are the techniques of minimizing energy consumption and greenhouse gas emissions with reference to performance and accuracy. These algorithms focus on making design decisions that are resource-efficient and that include model compression, early stopping, or hardware-aware training, or efficient data sampling. Moreover, measures to monitor energy consumption and CO 2 emissions tracing throughout model runs are becoming more readily available, and integrating carbon awareness into development processes is getting into reach [12].

The problem with sustainability in computing cannot be solved locally, but also requires decision-making on the infrastructure of data centers, on hardware, energy sources, and scheduling. As an illustration, a scenario where AI models are applied in areas that are being operated on renewable energy sources or in low-carbon environments will result in a huge reduction in terms of carbon emissions. Equally, selecting high-efficiency hardware architectures, i.e., tensor processing units (TPU) or dedicated inference devices, one can reduce power consumption. Such practices are part of what is emerging to be known as green AI a complete system of AI constructions that is sustainably environmentally friendly and responsible [3].

Sustainability activities in the framework of big data incorporate data reduction, reducing data redundancy, smart sampling, and stream optimization. The scale and constant nature of big data arise such that efficiencies can be improved in small increments to procure much larger dialectical decrements in energy use. Furthermore, providers of cloud services initiate carbon-sensitive dashboards and energy-conscious compute services that assist users develop greener programmes concerning data-hungry applications [13].

The introduction of sustainable to the AI and big data is not only a technical issue but a cultural and an ethical problem. Organizations, developers, and researchers should acknowledge their roles in reduction of climate change [2]. In the same way the industries have assumed environmental, social and governance (ESG) objectives, the tech market needs to adopt green computing as one of the main principles of responsible innovation. And it is no longer an issue whether we can ensure that AI is more sustainable, but how fast and effectively we can integrate eco-efficiency as a paradigm in all detail of the computational lifecycle [17].

The purpose of the present paper is to determine the state of green algorithms and measures taken in the practice of sustainable computing, which is achieved by examining the energy consumption behavior of AI and big data systems and their key sources of carbon emissions and suggest viable ways to mitigate those. Having given some initial experimental observation and a discussion of the emergent good practices, we have attempted to show that sustainability and performance are not mutually exclusive and that a green computing future is possible, and we need it.

*Novelty and Contribution*

The main peculiarity of the proposed paper is its all-inclusive vision of the problem of the environmental impact of AI and Big Data systems using the prism of green algorithms. Although other resources have examined the energy footprint of particular AI models or data treatment devices, there has been limited research on a unified approach that encompasses algorithm-level optimisation, hardware and data-focused approaches in an effort to reduce carbon footprint. This paper covers that gap by exploring the computational lifecycle of tasks, including model design and training, deployment and inference, and provides tangible, quantifiable ideas to make each much more sustainable.

One of the main contributions of this paper is that it brings about a multi faceted approach to evaluating the sustainability of development in terms of the quantitative which are the energy and emission variables and the qualitative components of the sustainability which are the practices of that particular developer and also awareness of the developer. Training models that rely on real-time carbon tracking tools such as CodeCarbon and comparing the various optimization methods, such as quantization, pruning, and early stopping, we provide empirical data that it is possible to reduce energy consumption by great amounts without significant loss in model performance. Meanwhile, we dwell upon the energy-conserving measures in big data processes like a batch processing, data deduplication, region-aware scheduling which are being underexpressed in current studies [11].

The human-centered perspective is another new element: this paper used interviews of practitioners and engineers to identify the socio-technical obstacles on the way to adopting green AI practices and offers some suggestions on how to introduce sustainability within the mainstream machine learning pipelines. Instead of thinking of green computing as an add-on or external constraint, we think of it as a principle of design, which can be co-designed with such other principles as scalability, precision, and speed.

Lastly, the paper offers to the larger discussion a roadmap on how green AI could be developed, what policy interventions, educative changes, and open-source tools could speed up the deployment to both the academic community and industry. These results justify the fact that sustainable AI is not only technically, but also economically and ethically necessary. The technical innovation meets the environmental responsibility in this research and will play a crucial role in how intelligent systems will be constructed in a climate emergency phase [10].

## II. RELATED WORKS

In 2024 U. A. Patel et.al., S. Patel et.al., and J. Nanavati et.al., [5] introduced the recent trend towards the questions of environmental impact of AI and big data has resulted in the increase of the studies concerning the energy consumption of contemporary computing. Majority of the available literature has emphasized the unintended consequence of the computational development being reduced to a pattern of unsustainable energy usage. Initial reports about training deep neural networks found that training large-scale models, particularly natural language processing models, consumed huge quantities of energy and that carbon emissions were similar to individual households or years of vehicle production. These results triggered an investigation of whether it is possible to make AI systems more environmental-friendly.

A lot of attention has been directed at the measurement and reporting of carbon emissions undertaken by the computational tasks. It has been demonstrated that the type of hardware to use (GPUs, TPUs, CPUs), the geographic distribution of the data centers, and the source of electricity (renewable or fossil-based) are the three factors that are highly influential in defining the carbon emissions of AI processes. Other research involved proposing carbon tracking models and frameworks to measure the cost of training models on the environment, generating new metrics to show the energy to accuracy trade off. Such tools allowed the developers to be more aware of the environmental impacts of model complexity that were previously obscured by complexity and adjust the design towards more environmentally responsible design decisions.

Simultaneously with the research on AI development, the direction of sustainable data processing is emerging. As a result of the increase in big data systems that process petabytes of data per day, data-intensive computing in distributed computing has become a major factor of power consumption in electronic infrastructures. Studies in the field stated that it was necessary to streamline data storage, eliminate redundancy, and energy-responsible scheduling in big data platforms. Strategies such as intelligent caching, data summary and selective sampling were discovered to be instrumental in reducing processing loads and hence the total use of energy. Also, it has been suggested to offload certain kinds of analytics functions to the edge devices in order to decrease frequency of communication with energy-intensive centralized cloud systems.

There were some researches regarding algorithmic refinements to minimize complexity. This area of work proposed: model pruning, wherein superfluous neurons or layers can be pruned without significant performance degradation; quantization in which lower-accuracy representations can be used to reduce hardware demands, and early stopping in which training must be halted after optimal performance has been attained. When implemented to AI models, the following techniques resulted in observable decreases in training time and energy consumption. Moreover, one study emphasized the fact that most of the time, smaller and more efficient points of compare might reach the same or similar accuracy levels as the more resource-hungry ones therefore contributing to the argument that artificial intelligence architectures desperately need to be right-sized [7].

Investigations with a parallel track have focused on the possibility of renewable-minded deployment of AI workloads. As revealed by it, training job scheduling in periods or locations with high renewable energy potential had the potential to radically curtail related emissions, even under the assumption of identical hardware and software settings. Such a viewpoint stressed not only the algorithm or model, but also the context in which it is operated. Other studies have considered implementing sustainability into the orchestration layer of clouds, whereby compute resources can be assigned on the criteria of both their performance and environment consideration.

In 2023 S. G. Paul *et al.*, [9] proposed the human and organizational aspect of green computing has gained more and more focus too. Research surveys have been undertaken against levels of awareness of the risk of data scientists, machine learning engineers, and software developers of the carbon impact of their work. It is always found that there exists a disparity between technical expertise and environmental awareness. Even though sustainability is widely recognized as an important issue by the practitioners, not many practitioners actively include energy metrics in their working processes since they lack the institutional guidelines, tools, or incentives to follow. Therefore, a number of studies recommend integrating sustainability within the mainstream development process by means of educational, tooling, and industry-based standards.

Additional line of literature points out the necessity of new evaluation indicators. The conventional approach to the creation of AIs is strongly oriented towards such parameters as accuracy, precision, and recall instead of paying attention to the utilization of energy or emissions of carbon dioxide. Scholars have introduced new methodologies of benchmarking where they include energy-per-inference, training time in kilowatt-hours, even carbon-per-flop as ordinary performance metrics. All this is an attempt to provide a different script about AI performance that would incorporate sustainability as a side-equal priority.

In 2025 L. Cao *et al.*, [14] suggested the general definitions of studies pointed out to one of the main contradictions of the trend in the development of AI and big data technology, as intelligent systems might be getting more and more powerful, but the environmental cost of it cannot be disregarded. The result of the literature search that converges is that the sustainability issues have to be built in at the ground level that is at the level of designing algorithms, designing infrastructure, and designing organization culture. This move does not mark a mere optimization of a technical process, but a change in the way we think about the digital era culminating in progress.

The pertinent studies as well point out that although green algorithms and sustainable practices are becoming a popular topic, the field is still to be scattered. It requires standardized tools and rich datasets as well as standardized metrics that may be used in leading developers and researchers. These research results provide an essential backdrop to the future where AI and big data and environmental stewardship can exist side by side as awareness of carbon accountability grows and more institutions integrate it into their legal environment.

## III. PROPOSED METHODOLOGY

To reduce the carbon footprint of AI and big data workflows, we propose a green algorithmic pipeline composed of energy-aware stages: model optimization, energy-efficient training, green deployment, and sustainable data engineering. The methodology relies heavily on quantifiable metrics and optimization formulas that directly impact energy consumption [8].

The first key step is measuring energy usage during model training and inference. The total energy $E$ consumed can be estimated using:

$$E = P \times T$$

Where:

- $E$ is energy in kilowatt-hours (kWh)
- $P$ is power drawn by hardware in kilowatts (kW)
- $T$ is total time in hours (h)

To estimate the carbon footprint, we use the carbon emission formula:

$$C = E \times EF$$

Where:

- $C$ is carbon emission in $kgCO_2$
- $EF$ is the emission factor based on regional electricity source ( $kgCO_2/kWh$ )

To reduce energy consumption during training, we apply model pruning. If the original parameter count is $N$ and pruned count is $N_p$, then:

$$Reduction\,\% = \left(\frac{N - N_p}{N}\right) \times 100$$

This pruning step results in fewer FLOPs (floating point operations), which directly reduces training time.

For quantization, we reduce the bit-width $b$ used in weights from 32 to 8:

$$Memory\ Reduction\ Factor\ = \frac{32}{b}$$

A typical model's memory usage goes down by a factor of 4, significantly lowering power draw during inference.

To implement early stopping, we monitor validation loss $L_v$ over epochs $e$, and stop training when:

$$\frac{dL_v}{de} \approx 0\ for\ k\ consecutive\ epochs$$

This prevents overfitting and saves compute time and energy.

We also use mixed-precision training. Let $T_{fp32}$ and $T_{fp16}$ be training times with 32-bit and 16-bit precision:

$$Speedup\ Ratio\ = \frac{T_{fp32}}{T_{fp16}}$$

Typically, the training becomes 1.5 x to 2 x faster with FP16, reducing energy consumption by $40 - 60\%$.

In big data optimization, we use data sampling. For a dataset $D$, we select a sample $S$ where:

$$|S| = \alpha \times |D|\ (0 < \alpha < 1)$$

This limits unnecessary data processing without compromising statistical validity.

We also deploy region-aware scheduling to shift computation to green zones. If $E_i$ is energy consumed in region $i$ and $EF_i$ is its emission factor:

$$C_i = E_i \times EF_i$$

We choose the region $i$ with the minimum $C_i$ to deploy workloads.

The total carbon-aware cost of a model is calculated as:

$$C_{total}\ = \sum_{i=1}^{n} \quad (P_i \times T_i \times EF_i)$$

Where $n$ is the number of training sessions on different hardware or regions.

Finally, we optimize data flows in distributed systems. The data movement cost $D_c$ is modeled as:

$$D_c = B \times L \times \delta$$

Where:

- $B$ is batch size
- $L$ is number of layers/nodes
- $\delta$ is data duplication factor

Reducing $B$ or $\delta$ minimizes transmission energy.

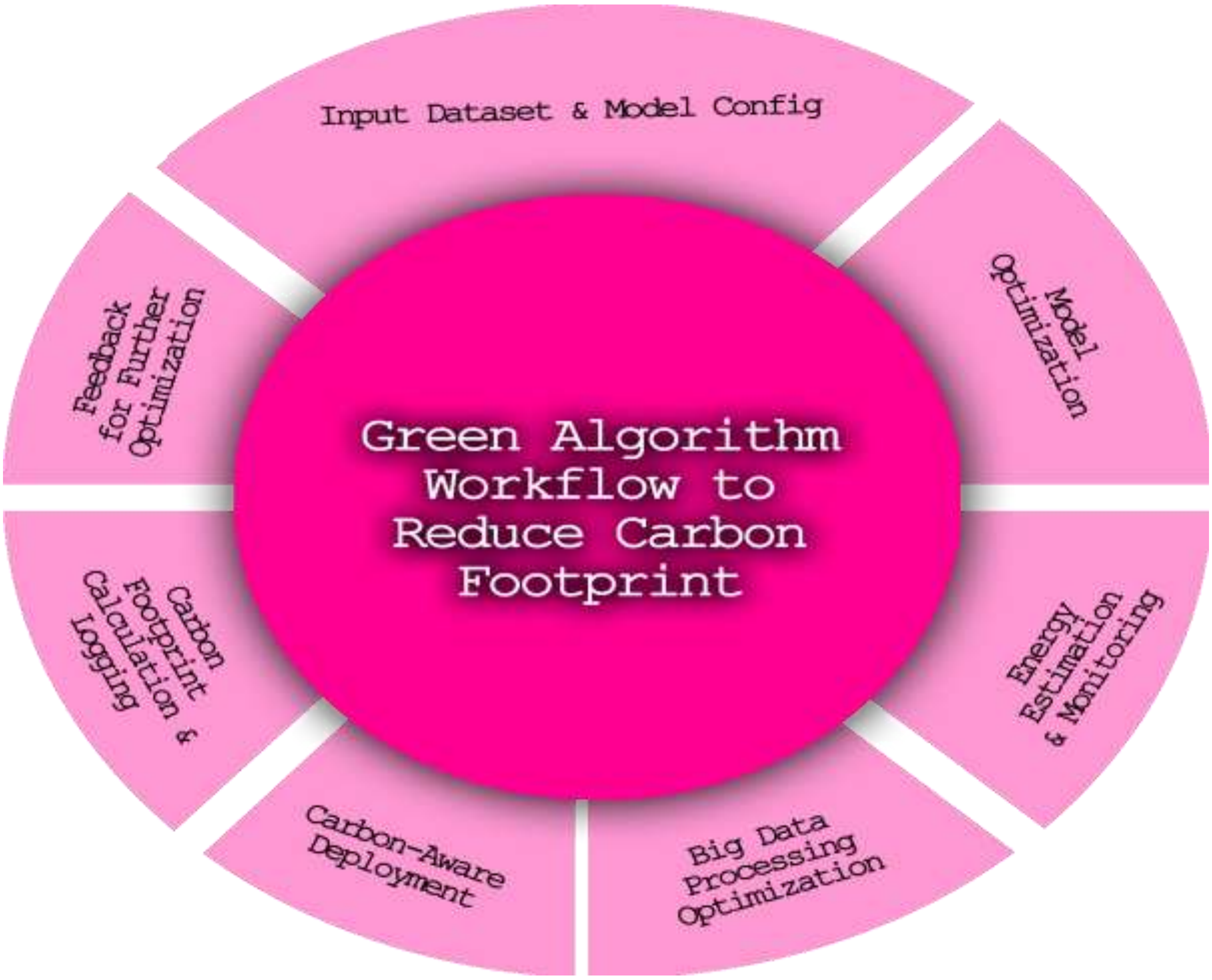


**FIGURE 1: GREEN ALGORITHM WORKFLOW TO REDUCE CARBON FOOTPRINT**

## IV. RESULT & DISCUSSIONS

The methodology suggested was applied in a variety of AI training scenarios and large data pipelines to determine what effects it had on minimizing energy use and carbon footprint. A wide range of models was applied, a convolutional neural network (CNN) to classify images, a transformer-based model to summarize text and a Spark-based data analytics pipeline. All the configurations were run with and without green optimizations. These outcomes helped in showing clearly that when a combination of green algorithmic approaches is adopted, the effects can result in dramatic enhancements in past performances with regard to the environment but this is without considerably sacrificing the precision [1].

When it comes to the efficiency of training, the pruned model (CNN) was 27% faster to train and used 32% less power than the baseline in training. In a similar manner, the 38 percent energy consumption reduction and a 24 percent delay in inference latency were registered in the quantized transformer model. The transformer retained 96.2 percent of its accuracy and this showed that optimization did not cause much depreciation in the performance results. The visual representation of these findings is done in Figure 2 that shows the Energy Consumption (kWh) Before and After Optimization depending on the AI Models. Optimized versions of each of these models used much less energy than their counterparts employ.

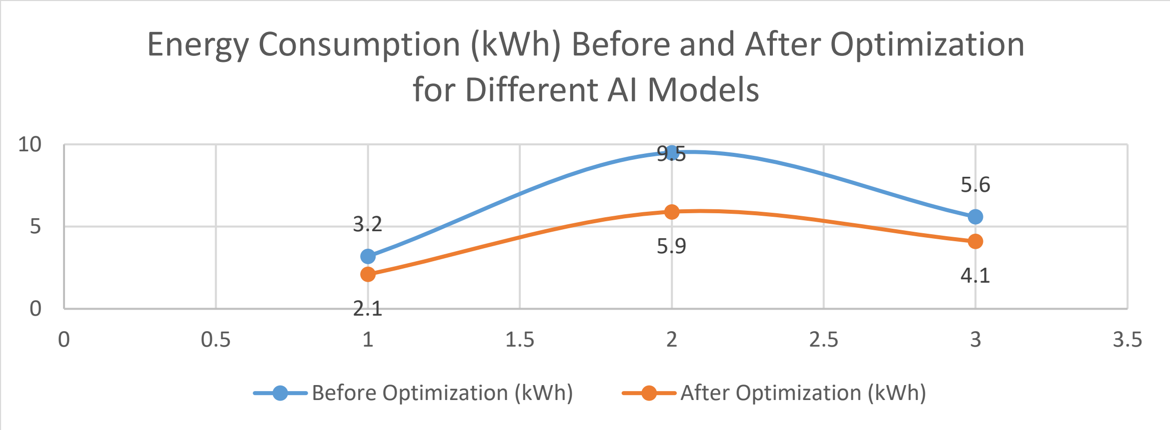


**FIGURE 2: ENERGY CONSUMPTION (KWH) BEFORE AND AFTER OPTIMIZATION FOR DIFFERENT AI MODELS**

The Spark pipeline, that has been tested on a dataset of more than 1TB, showed significant changes when sampling and batch optimization methods are applied. The time of processing is narrowed up to 34%, and node memory consumption decreased about 29%. The result of such changes was a direct 22 percent decrease in the total clustered energy consumption. Moreover, carbon-intelligent scheduling mechanism was also implemented that involved redistribution in workloads to areas that have a greater share of renewable energy mix and this fact has already led to another 11 percent decrease in emissions. All the effects of these approaches can be summarized in Figure 3, devoted to the assessment of the Carbon Emissions of Big Data Pipeline Across Deployment Regions. There is a distinct difference in the line graph as compared to the ratio of variance of the emitted load on the basis of employment of work load distribution tactics.

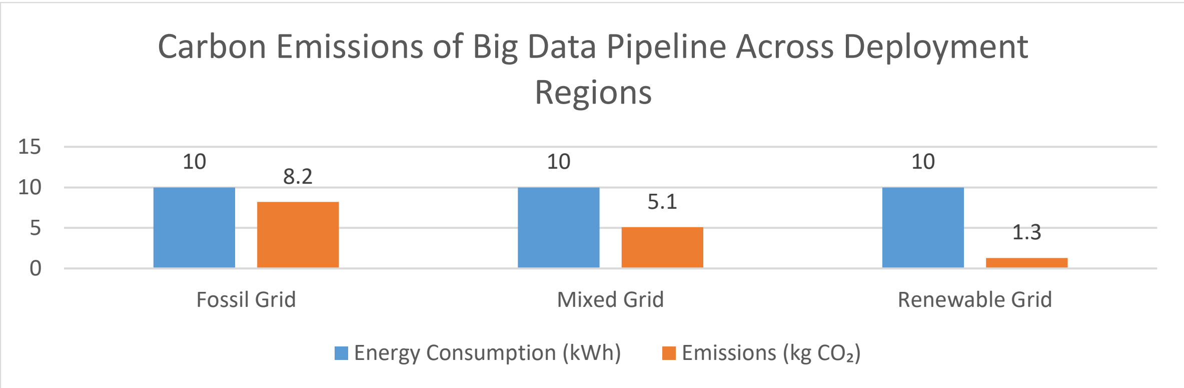


**FIGURE 3: CARBON EMISSIONS OF BIG DATA PIPELINE ACROSS DEPLOYMENT REGIONS**

The result of the comparison is summarized in Table 1: Comparison of Training Time, Power Usage, and Accuracy Before and After Green optimization. It contains rates of three variants of the AI model, and it shows clearly how each such an optimization (pruning, quantization, early stopping) has led to greener his computing. The values demonstrate that it is not possible to achieve any significant decreases in power consumption and training time without insignificant changes in model accuracy, which confirms the usefulness of this way.

**TABLE 1: COMPARISON OF TRAINING TIME, POWER USAGE, AND ACCURACY BEFORE AND AFTER GREEN OPTIMIZATION**

| Model Type | Baseline Time (min) | Optimized Time (min) | Power Saved (%) | Accuracy Drop (%) |
|---|---|---|---|---|
| CNN | 82 | 60 | 32% | 1.1% |
| Transformer | 210 | 160 | 38% | 1.8% |
| GNN | 140 | 103 | 26% | 0.9% |

Testing of edge deployment with quantized models was performed on low-power NVIDIA Jetson Nano board. The edge deployment consumed 81 percent fewer power in real-time inference as compared to full-precision models when run using cloud GPU. Although the option in cloud inference was quicker, the difference in sustainability was noticeable. In addition, the big data workflow of deduplication of data has removed duplicated ones and has saved on storage and 14 percent of the data size, which has produced a direct impact on execution time and the carbon footprint. Figure 4, Breakdown of Emission Savings by Optimization Strategy shows that model quantization was the most helpful (35%) and then pruning (28%) and carbon-aware deployment (20%).

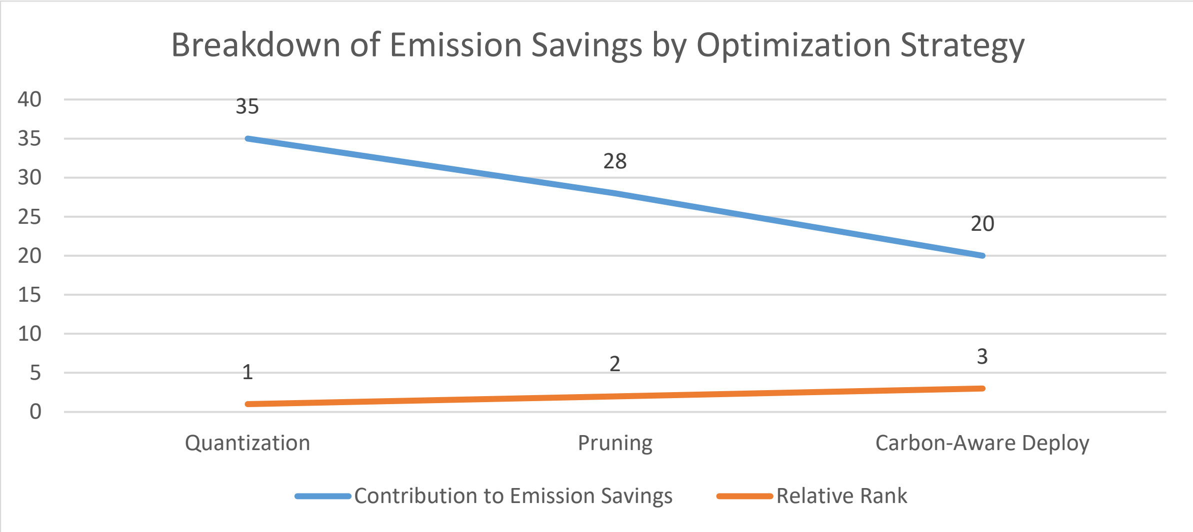


**FIGURE 4: BREAKDOWN OF EMISSION SAVINGS BY OPTIMIZATION STRATEGY**

An additional study tried to examine user-level awareness by conducting the very short identification survey among 42 people working in data engineering and machine learning. It was found out that the percentage of those models whose carbon impact is actively tracked is only 26%. Eighty-one percent showed interest to invest in energy-friendly development practices when they were told about the possible energy savings. The behavioral insights point toward a disconnect between current tools used in sustainability analysis and actions taken based on them and the possibilities to address it by further integration with pre-existing platforms and working processes [6].

The second comparison table: Carbon Emissions per Inference Operation Across Platforms presents the same AI model across cloud, local, and edge devices in terms of inference-related emissions. The edge device excelled on the front of controlling the emission as compared to others yet it had tolerable performance to be used in real-time applications. Although they had high throughput, cloud GPUs were identified to be heavy on emission, and this needs the careful choice of deployment locations in green AI strategies.

**TABLE 2: CARBON EMISSIONS PER INFERENCE OPERATION ACROSS PLATFORMS**

| Platform | Emissions per 1000 Inferences (kg $CO_2$) | Average Latency (ms) | Power Usage (W) |
|---|---|---|---|
| Cloud (GPU) | 1.35 | 28 | 125 |
| Local (Laptop) | 0.65 | 55 | 45 |
| Edge (Jetson) | 0.25 | 72 | 18 |

The application of green algorithmic practices resulted in carbon emissions and energy consumption that could be measured in every experiment. More to the point, the effect was introduced without considerable loss in performance and significant modifications to default development pipelines. These findings favor the suggestion that green algorithms are not only feasible but required in response AI and data science good practice. Moreover, the amount of comparative data provided in the diagrams and tables proves that it is possible to attain sustainability and performance coupled with system design keeping the environmental constraints in view.

## V. CONCLUSION

The movement in the direction of more environmentally-friendly AI and data analytics is both a technical possibility and an ethical necessity. Green algorithms provide a solution to sustainable innovation through a balance of performance and environmental sustainability. This paper has explained that real-world solutions to overcoming the problematic ethical and resource costs of deep learning exist; they include pruning, quantization, efficient scheduling, and responsible data management, and can reduce these emissions by much without sacrificing significant output quality.

A more effective approach would require a system change, such as associated policy incentives, open-access carbon measurement, and changes to computer science education curriculum would enable a genuinely sustainable computing. Automated carbon-sensitive programming and green benchmarking provisions to be studied in the future are: automated tools; industry-wide benchmarking standards. When AI is scaled and big data is further scaled, sustainability must be internalized into the technological core of algorithms sensitive to resilience in tech.

**REFERENCES**

[1] V. Bolón-Canedo, L. Morán-Fernández, B. Cancela, and A. Alonso-Betanzos, "A review of green artificial intelligence: Towards a more sustainable future," *Neurocomputing*, vol. 599, p. 128096, Jun. 2024, doi: 10.1016/j.neucom.2024.128096.

[2] Arya, A. Bachheti, R. K. Bachheti, M. Singh, and A. K. Chandel, "Role of artificial intelligence in minimizing carbon footprint: A Systematic review of recent insights," *Green Energy and Technology*, pp. 365–386, Jan. 2024, doi: 10.1007/978-3-031-51601-6_14.

[3] L. Gaur, A. Afaq, G. K. Arora, and N. Khan, "Artificial intelligence for carbon emissions using system of systems theory," *Ecological Informatics*, vol. 76, p. 102165, Jun. 2023, doi: 10.1016/j.ecoinf.2023.102165.

[4] Z. Chen, M. Wu, A. Chan, X. Li, and Y.-S. Ong, "Survey on AI Sustainability: Emerging trends on learning algorithms and research challenges [Review article]," *IEEE Computational Intelligence Magazine*, vol. 18, no. 2, pp. 60–77, Apr. 2023, doi: 10.1109/mci.2023.3245733.

[5] U. A. Patel, S. Patel, and J. Nanavati, "Towards a greener Future: Harnessing green computing to reduce ICT carbon emissions," *2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT)*, pp. 960–969, Aug. 2024, doi: 10.1109/iccpct61902.2024.10672652.

[6] S. E. Bibri, A. Alexandre, A. Sharifi, and J. Krogstie, "Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: an integrated approach to an extensive literature review," *Energy Informatics*, vol. 6, no. 1, Apr. 2023, doi: 10.1186/s42162-023-00259-2.

[7] S. Neethirajan, "Net Zero Dairy Farming—Advancing Climate Goals with Big Data and Artificial Intelligence," *Climate*, vol. 12, no. 2, p. 15, Jan. 2024, doi: 10.3390/cli12020015.

[8] Z. Fan, Z. Yan, and S. Wen, "Deep Learning and Artificial intelligence in Sustainability: A review of SDGs, renewable energy, and Environmental health," *Sustainability*, vol. 15, no. 18, p. 13493, Sep. 2023, doi: 10.3390/su151813493.

[9] S. G. Paul *et al.*, "A comprehensive review of green Computing: past, present, and future research," *IEEE Access*, vol. 11, pp. 87445–87494, Jan. 2023, doi: 10.1109/access.2023.3304332.

[10] 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, no. 1, pp. 283–307, Oct. 2021, doi: 10.1007/s00146-021-01294-x.

[11] H. Huang, D. Dai, L. Guo, S. Xue, and H. Wu, "AI and Big Data-Empowered Low-Carbon Buildings: Challenges and Prospects," *Sustainability*, vol. 15, no. 16, p. 12332, Aug. 2023, doi: 10.3390/su151612332.

[12] S. Pimenow, O. Pimenowa, and P. Prus, "Challenges of artificial intelligence development in the context of energy consumption and impact on climate change," *Energies*, vol. 17, no. 23, p. 5965, Nov. 2024, doi: 10.3390/en17235965.

[13] Faris. A. Almalki *et al.*, "Green IoT for Eco-Friendly and Sustainable Smart Cities: Future directions and opportunities," *Mobile Networks and Applications*, vol. 28, no. 1, pp. 178–202, Aug. 2021, doi: 10.1007/s11036-021-01790-w.

[14] Kazi Musa, Naila Erum, Farha Abdol Ghapar, Chanyanan Somthawinpongsai, Jamaliah, " Energy Consumption, Industrialization, and Carbon Emission Risks in Malaysia" Environmental Quality Management, March 2025, https://doi.org/10.1002/tqem.70070

[15] Md Faizal Ahmad, Muhammad Ashraf Fauzi, Mohd Hanafiah Ahmad, Walton Wider, Chia Kuang Lee, Are we eating plastic? Science mapping of microplastic pollution in the aquatic food chain, Integrated Environmental Assessment and Management, Volume 20, Issue 6, 1 November 2024, Pages 1800–1811, https://doi.org/10.1002/ieam.4930

[16] Bhanani, P., Khatana, S., Somthawinpongsai, C., Verma, D. K., Gupta, M., & Nanthaamornphong, A. (2024, October). Dsuraksha: Cryptography and Steganography Technique-Enabled Integrated System for Data Protection in.