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Advancing Sustainable AI: Balancing Performance and Carbon Emissions with System of Systems Theory

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Abstract: ***Artificial intelligence (AI) can reduce and increase a company's carbon footprint. This study explores this complex relationship. AI techniques can be used to fight climate change, but training these models can consume a lot of energy. Here, we examine AI and carbon emissions as interconnected systems. We analyzed six machine learning models and calculated their carbon footprint. Our goal is to promote "sustainable AI" where environmental responsibility is considered throughout the development process, from data collection to using the model. By advocating for sustainable practices, we encourage the creation of effective AI that's also eco - friendly.***

Keywords: Sustainable AI, Machine Learning, Carbon Emissions, Energy Efficiency, Green AI, Deep Learning

1. Introduction

Artificial intelligence (AI) is revolutionizing our world, and its impact on the environment is a complex issue demanding our attention. While AI offers a beacon of hope for sustainability through advancements in resource management and environmental monitoring, it also carries a hidden burden: the generation of carbon emissions. The immense energy needed to train and run complex AI models comes at a cost to our planet.

This research tackles this critical duality. Earlier studies have often focused on the positive environmental contributions of AI. We aim to provide a more comprehensive understanding by exploring both the positive and negative environmental consequences of AI technologies. A key focus will be finding machine learning models that create a lower carbon footprint. To achieve a holistic perspective, we will employ a System of Systems (SoS) approach. This framework views AI and carbon emissions as interconnected parts of a larger system. By analyzing these interactions, we can develop strategies to make AI practices more sustainable. This research proposes a framework for achieving this goal, ultimately paving the way for a future where AI helps us achieve environmental sustainability without compromising the health of our planet. Furthermore, we believe it is crucial to consider the ethical implications of AI research in the face of climate change. Researchers should not only strive for model accuracy but also factor in the energy costs associated with development. By incorporating these considerations into research practices, we can ensure that AI becomes a responsible tool for environmental progress.

The High Energy Cost of Deep Learning and the Need for Sustainable Practices

Deep learning (DL) algorithms are powerful tools with a wide range of applications, but their training process comes at an environmental cost. Training these complex models requires vast amounts of computing power, which translates to significant energy consumption. This high energy demand leads to copious quantities of carbon dioxide, a major climate change contributor. While DL holds promise for tackling some of the world's most pressing problems, it's crucial to acknowledge and address its environmental impact. Researchers are actively exploring the limitations and drawbacks of DL in the context of climate change.

One key approach to understanding this issue is through a Systems of Systems (SoS) lens. This perspective views DL and carbon emissions as interconnected parts of a larger system. Earlier studies have successfully applied the SoS approach to analyze the environmental impact of energy production systems. By taking this broader view, researchers can develop effective strategies to reduce greenhouse gas emissions associated with DL. Another strategy involves exploring alternative machine learning algorithms. Deep learning is just one type of machine learning, and there are other algorithms that may achieve comparable results with less computational power. Some examples include K - Nearest Neighbors, Linear Regression, and Decision Trees. By carefully selecting the most suitable algorithm for a specific task, we can minimize the environmental footprint of AI technologies.

AI: A Double - Edged Sword for Environmental Sustainability

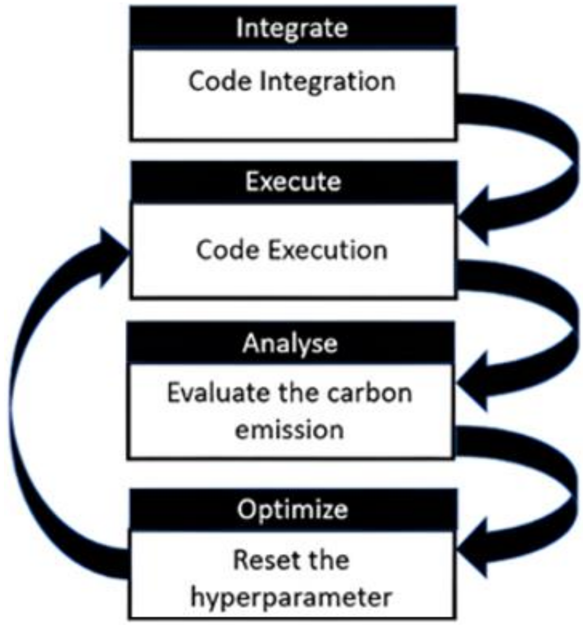
This study explores the complex relationship between Artificial Intelligence (AI) and the environment. While AI offers exciting possibilities for sustainability, it also presents a hidden cost: increased carbon emissions. The training and operation of complex AI models require vast amounts of computing power, and the energy consumption associated with this process translates to significant carbon dioxide emissions. Despite this drawback, AI has the potential to be a powerful tool in the fight against climate change. AI can be used to perfect energy usage in buildings and factories, leading to reduced energy waste and greenhouse gas emissions. Additionally, AI can analyze vast datasets on wildlife, forests, and oceans, empowering us to make better decisions about conservation and resource management.
Researchers have found several areas where AI can contribute to environmental sustainability. For instance, AI - powered self - driving cars, by deciding the most efficient routes, can

lower pollution levels in our cities. AI - driven data analysis can also enhance accountability by tracking whether governments and businesses are meeting their emission reduction targets. AI can even be used to predict dangerous weather patterns, allowing us to prepare for and mitigate the effects of climate change. However, to fully harness the potential of AI for environmental good, we must acknowledge and address its environmental impact. The high energy consumption associated with training and running AI models is a significant concern. These models often rely on supercomputers powered by the public electricity grid, which may not always use renewable energy sources. In some cases, backup diesel generators are used to keep power, further contributing to carbon emissions. Studies have shown that the training of a single AI system can generate carbon dioxide emissions comparable to those produced by the aviation industry. Therefore, we must strive to develop and implement sustainable AI practices. This could involve exploring methods to perfect AI model training processes to reduce energy consumption. Additionally, using energy - efficient hardware for AI development and deployment is crucial. Furthermore, selecting and designing AI models that prioritize lower carbon footprints while keeping necessary accuracy can significantly reduce the environmental impact of AI technologies.

In conclusion, AI presents a double - edged sword for the environment. While it offers powerful tools for tackling climate change, its own energy consumption creates environmental challenges. By acknowledging these drawbacks and actively implementing sustainable practices, we can ensure that AI development contributes to a greener future.

Quantifying the Carbon Footprint of AI Algorithms: A Methodology for Sustainable Practices

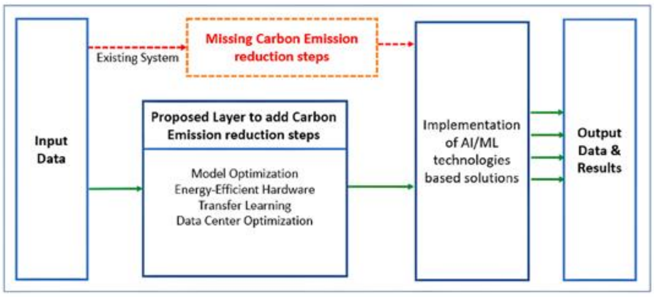
This section delves into the method employed in this research to evaluate the environmental impact of various AI algorithms. A key concern surrounding AI is the significant energy consumption associated with training and running complex models. This translates to carbon emissions, potentially undermining the environmental benefits that AI can offer. To address this concern, we designed an experiment to quantify the carbon footprint of different algorithms with varying levels of complexity. The cornerstone of our method is a software tool called CodeCarbon. This tool seamlessly integrates with Python scripts and calculates the carbon emissions generated by the code's execution, whether on a local system or in the cloud. Users start the process by calling on the relevant packages with a "tracker start" command, marking the starting point for emission calculation. Following this, the user adds the code itself, and concludes with a "tracker stop" command. These carbon trackers also offer functionalities to analyze the carbon footprint while adjusting hyperparameters like epochs and batch size, allowing us to assess the impact of different training configurations on environmental impact.



To quantify the carbon footprint, we use CO2 equivalent (CO2eq) - the standardized unit for greenhouse gas emissions. Carbon emissions are measured in kilograms of CO2eq, accounting for the varying warming potential of different greenhouse gases compared to carbon dioxide. The calculation for carbon emissions hinges on two key factors:

1) Carbon Intensity of Electricity (C): This is the number of kilograms of CO2 emitted per kilowatt - hour of electricity used for the computations. In essence, it reflects the "cleanliness" of the energy source powering the computational infrastructure.
2) Power Consumption (P): This signifies the amount of power consumed by the computational infrastructure during the execution of the code. This is measured in kilowatt - hours.

By multiplying these two factors (C x P), we arrive at the total carbon emissions generated in CO2eq for running a specific algorithm or code. This method allows us to precisely measure the environmental impact of different algorithms and guide the development of sustainable AI practices.



2. Results

The study investigates the carbon emissions associated with various machine learning (ML) algorithms, highlighting the environmental impact of training these models. The supervised ML algorithms, such as Decision Tree, Random Forest, and Support Vector Machine (SVM), show lower computational intensity. In contrast, deep learning (DL) models like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are more complex and result in higher carbon emissions due to their intensive computational requirements. The table below provides detailed data on carbon emissions for different ML algorithms. For instance, Decision Tree has a carbon emission of 2.328 x 10^ - 7 lb, Random Forest 0.024 x 10^ - 7 lb, and SVM 0.062 x 10^ - 7 lb. In comparison, DL models show significantly higher emissions: ANN emits 3378.045 x 10^ - 7 lb, and deepfake creation models emit a staggering 25, 463.778 x 10^ - 7 lb. The total carbon emission across all algorithms studied is 0.0032 lb.

The findings illustrate that simpler ML algorithms like Decision Trees and Random Forests are better suited for energy - efficient modeling of complex relationships in large datasets, aiding in energy consumption prediction, energy savings identification, and renewable energy optimization. Figures 5 and 6 in the study visually represent these findings, showing that larger and more complex models, such as those used in DL, require more computational resources, leading to higher energy consumption and carbon emissions.
To reduce the carbon footprint of ML models, several strategies are recommended:
1) Use Computationally Efficient Algorithms: Employing resource - constrained devices for edge computing and using quantization technologies can significantly reduce emissions.
2) Avoid Training from Scratch: Using pretrained models can dramatically lower the computational power needed, minimizing the carbon footprint.
3) Employ Automated ML: Selecting the most efficient model and quickly discarding ineffective ones can reduce computing costs and emissions.
4) Adopt Federated Learning (FL): FL methods can receive help from hardware advancements and reduce the need for energy - intensive cooling systems in data centers.

The study underscores the importance of considering environmental implications in AI and ML work, emphasizing the need for developing more efficient algorithms and training methods to minimize carbon emissions and energy consumption.

CodeCarbon provides visualizations of net power usage and emissions, equating them to everyday activities. For example, the total emissions from the six algorithms studied are equivalent to 4.79 minutes of watching an LCD television or driving a car up to 0.02 miles. The codes used in this study released 0.0014 kg of emissions, highlighting the environmental impact of widespread AI and ML integration.

Carbon emissions through ML algorithms.

Input Code	Epochs	Batch Size	Carbon Emission (in-lb) (e^{-7})
Decision Tree	100	50	2.328
Random Forest	100	50	0.024
Support Vector Machine Regression	100	50	0.062
K-Nearest Neighbor with multiple visualizations (Scatterplot, Pairplot, Heatmap, Bar graph, Histogram)	100	50	2173.208
Artificial Neural Network	100	50	3378.045
Deepfake Creation	100	50	25,463.778

The total Carbon Emission released is 0.0032 lb.

3. Discussion

This study emphasizes the System of Systems (SoS) approach to promote sustainable AI by considering the interactions and dependencies between various systems. Integrating sustainability aims into AI system design involves finding metrics like energy consumption, carbon footprint, and resource efficiency. As AI models become more prevalent across sectors, it is crucial to measure and minimize their energy use and emissions.

However, our findings differ from Chen et al. (2022), which focuses solely on AI's positive impact on reducing carbon emissions in specific contexts. Our study highlights AI's double - edged nature: while it can help mitigate environmental issues, it also has significant carbon emissions from computational costs. This is clear in the carbon emissions data for various algorithms, such as Decision Tree (2.328 x 10^ - 7 lb), Random Forest (0.024 x 10^ - 7 lb), SVM (0.062 x 10^ - 7 lb), ANN (3378.045 x 10^ - 7 lb), and deepfake models (25, 463.778 x 10^ - 7 lb), with a total emission of 0.0032 lb.

Henderson et al. (2020) also stresses the importance of tracking and reporting energy and carbon usage in machine learning research, promoting sustainable development. Today's AI research must shift toward its environmental impact. Despite the computational costs, achieving or surpassing current accuracy standards is still seen as an achievement. Thus, the AI research community must focus on combining energy efficiency with system accuracy to encourage environmentally sustainable AI.

Researchers should provide transparency about the computational cost of training algorithms. Tools that help companies check and limit carbon emissions from model training can pave the way for sustainable AI. Additionally, developing more effective techniques for training and deploying models should become standard practice for businesses and scholars. Promoting environmentally

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sustainable AI involves collaboration between researchers, industry, and government organizations. Open - source initiatives for sustainable AI can give best practices and ease collaboration. Governments should set standards and regulations to incentivize sustainable AI development, and investments in R&D for sustainable AI technologies are crucial. Increasing public education and awareness about AI's environmental impact can promote sustainable AI adoption. By advancing these efforts, AI can remain a powerful tool for combating climate change while minimizing its negative environmental impacts.

4. Conclusion

AI has the potential to both benefit and harm the environment, making sustainable AI practices crucial throughout its lifecycle. While deep learning models are necessary for certain tasks, simpler machine learning algorithms can often achieve comparable results with less computational power and energy, making them more environmentally responsible. As climate change impacts become increasingly severe, researchers must consider the ethical implications of their AI work and strive to reduce its carbon footprint.

This study underscores the importance of integrating sustainability into AI development, emphasizing energy efficiency and minimizing carbon emissions. By adopting tools for monitoring and limiting emissions, using pretrained models, and prioritizing resource - efficient algorithms, the AI community can significantly reduce its environmental impact. Collaboration among researchers, industry, and policymakers, along with public education, is essential to drive the adoption of sustainable AI practices. Future research should focus on developing green technologies, incorporating economic rationales, and employing design thinking to achieve zero emissions from AI applications. Ultimately, responsible and sustainable AI is not only about technological advancement but also about ensuring that AI serves as a tool for environmental governance and sustainability. By doing so, AI can help combat climate change while minimizing its own negative environmental effects.

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