Sustainable Machine Learning: Evaluating the Environmental Cost of AutoML Algorithms in AI Development

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***Abstract*—This study evaluates the carbon footprint (CF) of Automated Machine Learning (AutoML) algorithms in AI development, examining three datasets to assess emissions across various run-times and countries. It is shown that the carbon intensity (CI) of these systems is significantly influenced by the energy sources powering the computational infrastructure. A correlation between run-time and model accuracy is observed, showing diminishing returns in accuracy with increased run-time and its environmental cost. The findings highlight the crucial role of geographic location and regional energy mix in determining the carbon footprint of AI operations. In areas with low-carbon or renewable energy sources, AI systems exhibit a reduced carbon footprint, underscoring the importance of infrastructural and environmental context in AI's ecological impact. This study calls for adopting energy-efficient locations and optimizing ML algorithms to achieve a balance between model accuracy and environmental costs.**

***Index Terms*—Carbon Footprint; Sustainability; Machine Learning; AutoML**

I. Introduction

In an era where carbon footprint (CF) and sustainability are at the forefront of global priorities, the urgency to achieve net-zero targets is paramount. The European Union and other influential bodies have set ambitious goals, pressing for a rapid transition to a more sustainable future. Thus, corporations worldwide are increasingly cognizant of their environmental responsibilities. Within this context, the role of Artificial Intelligence (AI) and Machine Learning (ML) becomes particularly significant. As these technologies continue to drive innovation across various sectors, their energy-intensive nature brings a crucial aspect into focus: the importance of taking sustainability seriously in AI/ML development [1].

This paper evaluates the CF of ML algorithms in AI development using an automated machine learning (AutoML) setup. The study analyzes the CF across several datasets, run-times, and geographic locations to understand how these factors affect emissions. It also investigates the relationship between model accuracy, run-time, and environmental cost, and assesses the impact of regional energy mixes on AI operations' CF. The findings stress the need for sustainable AI practices, advocating for energy-efficient locations and optimized AutoML algorithms to balance model accuracy and environmental impact.

II. Methods and Materials

A. Carbon Footprint Measurement

The concept of a "carbon footprint" encompasses the entire spectrum of greenhouse gas emissions, including those from activities like driving a car, manufacturing goods, or training an ML model. To calculate the CF, the formula used is:

$$\text{CO}_2 \text{ Emissions} = E \times C. \tag{1}$$

In this equation, E symbolizes the electricity used during a specific computational task, measured in kilowatt-hours (kWh). C stands for the carbon intensity of electricity, indicating the amount of CO2 produced per unit of electricity, given in kilograms of CO2 per kilowatt-hour. It's important to note that carbon intensity is not constant; it varies according to the region, reflecting the diversity of energy sources used.

For assessing the CF of ML models, the energy consumption of the computing resources was recorded throughout the training phase. The Intel Power Gadget was employed for this purpose. This tool tracks processor energy consumption in real-time, measured in mWh. This value was then converted into kilowatt-hours (kWh). The final step in estimating the carbon emissions involved multiplying this energy consumption by the carbon intensity of the electricity, where the carbon intensity is typically reported in kilograms of CO2 emitted.

B. Automated Machine Learning

This study employed an AutoML setup, which streamlines the process of developing ML models by automating several key steps: preprocessing of data, model training, evaluation, and selection. This approach reduces the complexity and expertise required to build models, which accelerates model development and helps to build more robust and accurate models. AutoML democratizes ML by enabling users with limited data science background to create effective models [2].

C. Experimental Design

This study used three datasets, as detailed in Table I. Preprocessing included under sampling for the following classification task, while H2O AutoML managed all other data processing tasks, including model tuning, evaluation, and selection.

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TABLE I
DESCRIPTION OF DATASETS

Dataset	Observations					Description
	Total	$y = 0$	$y = 1$	Balanced	Features	
Credit Risk	30,000	23,364	6,636	6636/6636	23	Prediction whether a customer is going to default on their credit card payment
Marketing	45,211	39,922	5,289	5289/5289	16	Prediction whether a targeted customer will open a deposit account after a direct marketing effort
Cybersecurity	25,192	13,449	11,743	11,743/11,743	41	Prediction of whether network traffic is usual behavior or should be categorised as an attack

TABLE II
COMPARATIVE ANALYSIS OF AUTOML PERFORMANCE AND ENVIRONMENTAL IMPACT ACROSS VARIOUS DATASETS AND COUNTRIES

Dataset	Prediction Accuracy (%)		Processor Energy (mWh)		Location	CI (g CO2/kWh)	Carbon Footprint (kg CO2)	
	60	120	60	120			60	120
Credit Risk	72.5	72.6	534	926	Germany	385	0.2057	0.3565
					France	85	0.0454	0.0787
					Spain	217	0.1159	0.2009
Marketing	79.7	79.6	574	891	Germany	385	0.2210	0.3430
					France	85	0.0488	0.0757
					Spain	217	0.1246	0.1934
Cybersecurity	99.7	99.7	541	907	Germany	385	0.2083	0.3492
					France	85	0.0459	0.0771
					Spain	217	0.1174	0.1968

III. RESULTS

The results indicate variations in the CF of ML algorithms based on the geographic location's energy sources. Accuracy levels are largely the same for various runtimes. These outcomes are presented in Table II, which outlines the AutoML performance metrics, including energy consumption and CF, across multiple datasets and locations.

IV. DISCUSSION

The findings of this study underscore the dependence of the CF of AI algorithms on the carbon intensity of the geographic location.

[1] Regional Energy Mix: The analysis reveals that AI algorithms operating in regions predominantly powered by fossil fuels exhibit a higher CF compared to those in areas with a larger share of renewable energy sources. This variation emphasizes the critical role of the regional energy infrastructure in determining the environmental impact of AI operations.

[2] Policy and Infrastructure Implications: The findings suggest that policymakers and AI practitioners should prioritize the development and utilization of AI infrastructure in regions with cleaner energy sources. This could involve locating new data centers in areas with low-carbon energy supplies or investing in renewable energy sources in regions with high computational demands.

[3] Balancing Accuracy with Environmental Costs: The study also examines the trade-off between model accuracy and environmental cost, noting diminishing returns with longer runtimes and emphasizing the need to balance incremental accuracy gains against their ecological impact.

V. CONCLUSION

This study highlights that the carbon footprint of ML algorithms significantly depends on the carbon intensity of their geographic location, emphasizing the need for a holistic approach to AI development that integrates environmental sustainability as a fundamental component when setting up AI/ML operations. However, the study's implications extend beyond just reducing energy consumption in AI applications; it highlights the broader necessity of transitioning towards renewable and cleaner energy sources globally. This transition is key to reducing the overall carbon footprint, not only in the field of AI but across all sectors that rely on energy-intensive processes.

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