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Engineering Carbon Emission-aware Machine Learning Pipelines

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Introduction

- The rapid advancement of **Artificial Intelligence (AI)** brings unprecedented technological growth.
- However, it also raises concerns regarding its **environmental impact**, especially carbon emissions.
- Our goal: To develop methodologies that balance **high AI performance** with **minimal environmental impact**.

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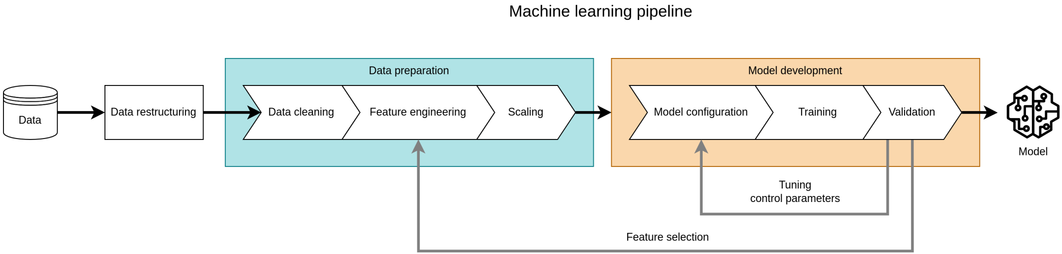
Our contributions

- **Novel sustainable ML pipeline**: CEMAI offers a new approach to ML development, *environmentally-conscious workflows*.
- **Empirical evidence**: Provides empirical evidence on the effectiveness of using carbon emissions as a metric for pipeline configuration and optimization.
- **AI engineering dimensions for sustainability**: Introduces new AI engineering dimensions focused on sustainability, including *energy measurement* and *carbon emission measurement*, fostering a shift towards more ecologically responsible AI engineering practices.

ML pipeline


Machine learning pipeline
Data
Data restructuring
Data preparation
Data cleaning
Feature engineering
Scaling
Model development
Model configuration
Training
Validation
Model
Tuning
control parameters
Feature selection

CEMAI concept

Two core concepts:

- **Green AI metrics**
- **Green pipeline orchestration**

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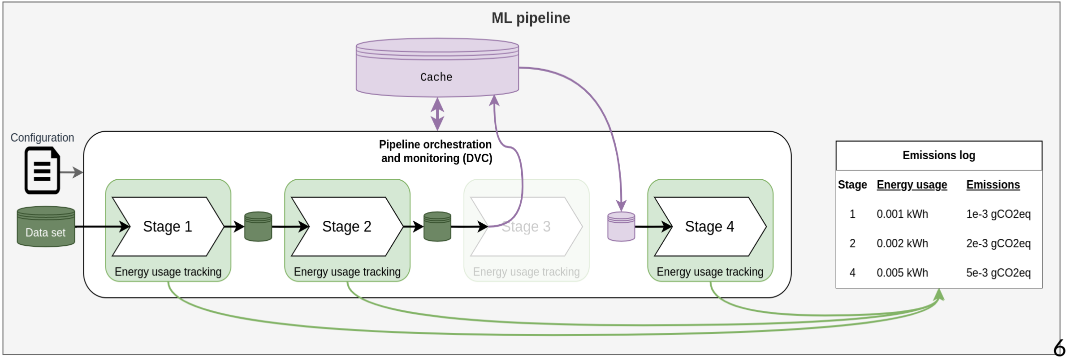
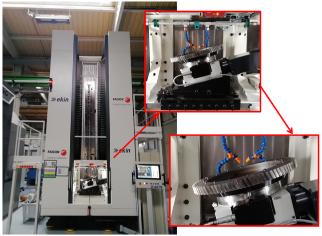


Experiments

- **RQ1**: What are carbon emissions in different stages of the pipeline and can they be optimized?
- **RQ2**: How does the choice of hardware affect the overall carbon emissions of the pipeline?

Experiment design

Dataset	Machine	Task	#Train	#Test
Piston Rod	Turning	Useful Lifetime	332,919	83,229
Broaching	Broaching	Tool wear	3,072,024	2,048,016
Bosch CNC	CNC	Anomaly	1,168,434	1,168,434



RQ1: What are carbon emissions in different stages of the pipeline and can they be optimized?

	Carbon emissions per stage (gCO_2eq)										
Model	Profile	Clean	Featurize	Split	Scale	Sequentialize	Combine	Train	Evaluate	Explain	Total	R^2
DT	0.1291	0.0197	0.0004	0.0001	0.0002	0.0021	0.0002	0.0113	0.0015	0.0601	0.2247	−1.22
DT w/FE	0.1291	0.0197	0.0083	0.0000	0.0000	0.0000	0.0002	0.0014	0.0015	0.0022	0.1625	0.91
RF	0.1291	0.0197	0.0026	0.0000	0.0002	0.0021	0.0002	1.1697	0.0000	0.0000	1.3237	0.76
RF w/FE	0.1291	0.0197	0.0083	0.0000	0.0000	0.0000	0.0002	0.0014	0.0017	0.0622	0.2227	0.83
GB	0.1291	0.0197	0.0034	0.0001	0.0003	0.0025	0.0002	0.1608	0.0059	0.0634	0.3859	0.12
GB w/FE	0.1291	0.0197	0.0083	0.0000	0.0000	0.0000	0.0000	0.0014	0.0018	0.0056	0.1662	0.92
XGB	0.1291	0.0197	0.0004	0.0001	0.0002	0.0021	0.0002	0.0336	0.0043	0.0829	0.1599	0.17
XGB w/FE	0.1291	0.0197	0.0055	0.0000	0.0000	0.0000	0.0000	0.0014	0.0015	0.0026	0.1599	0.70
DNN	0.1291	0.0197	0.0004	0.0001	0.0002	0.0004	0.0002	0.0317	0.0030	0.1631	0.3479	−10.80
DNN w/FE	0.1291	0.0197	0.0067	0.0004	0.0036	0.0009	0.0015	0.0430	0.0031	0.1835	0.3915	0.48
CNN	0.1291	0.0197	0.0004	6.1989	0.0002	0.0004	0.0002	0.0016	0.0015	0.0601	0.2134	−0.08
CNN w/FE	0.1291	0.0197	0.0067	0.0004	0.0013	0.0022	0.0040	0.2112	0.0044	0.1323	0.5112	−0.04
LSTM	0.1291	0.0197	0.0004	0.0001	0.0002	0.0004	0.0002	8.3925	0.0240	0.4471	9.0137	−0.01
LSTM w/FE	0.1291	0.0197	0.0083	0.0000	0.0000	0.0034	0.0004	11.0341	0.0240	0.3863	11.6053	−0.08

Figure: Broaching use case

RQ1: What are carbon emissions in different stages of the pipeline and can they be optimized?

- The **train** and **evalute** stages emit the most CO_2 in our datasets
- Feature engineering adds emissions but can improve performance, and reduce model complexity
- Incorporating Green AI metrics into the development process enables choosing *greener* models with adequate performance

RQ2 How does the choice of hardware affect the overall carbon emissions of the pipeline?

- Hardware choice has significant influence
- Laptops consistently exhibit lower carbon emissions than the cloud server in our experiments

		Carbon emissions (gCO_2eq)		
Case study	Model	Laptop (CPU)	Laptop (GPU)	Cloud
Piston Rod	RF	0.2502	0.1977	1.1420
Broaching	DT w/FE	0.1164	0.1625	0.6431
Bosch CNC	DT w/FE	0.0349	0.0271	0.1608

Future Work and Implications

- **Continual Learning**: Exploring the integration of continual learning to adapt models with minimal environmental impact.
- **Transfer Learning**: Leveraging transfer learning strategies to minimize retraining and computational resources, thus reducing carbon emissions.
- **Multi-objective Optimization**: Future directions include developing algorithms for optimizing both ML model performance and sustainability, balancing computational efficiency with ecological responsibility.

Conclusion

- CEMAI enables a balanced approach to ML model development
- Prioritizing both performance and reduced carbon footprint
- **Call to Action**: Encourages the adoption of CEMAI and similar practices to promote sustainability within the AI and machine learning fields.

Technology for a better society