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“ PCOG Lightning Talks” July 2023

# Data-Centric Green AI

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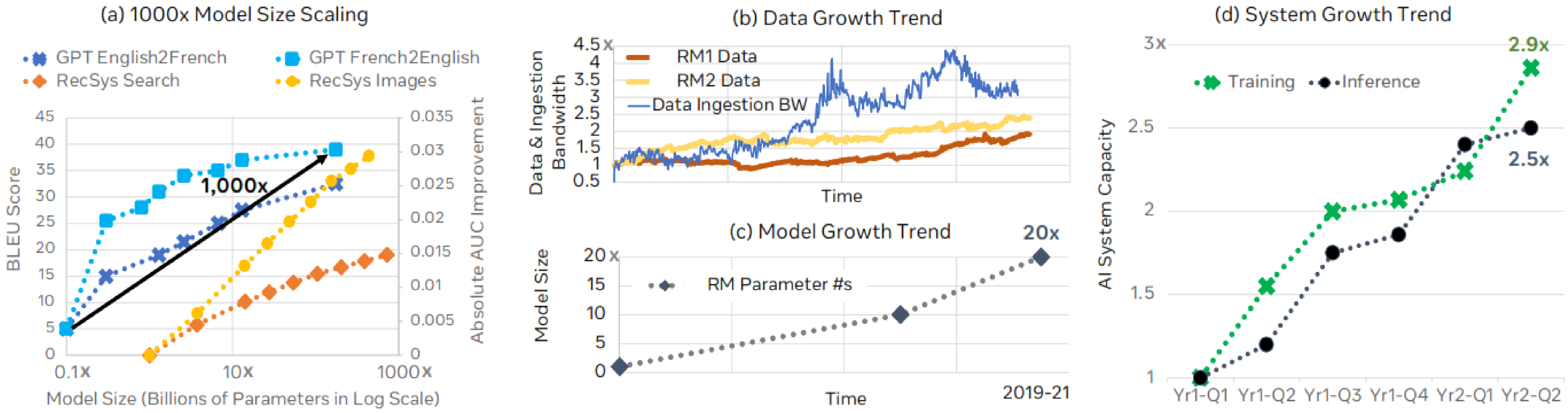
# AI Revolution

# AI Revolution




AI Data Growth

AI Model Growth

AI Infrastructure Growth

Deep learning has witnessed an exponential growth in data, model parameters, and system resources over the recent years. (a) The 1000× model size growth has led to higher model accuracy for various ML tasks. For example, with GPT-3, to increase the model quality BLEU score from 5 to 40 requires a model 1000× larger in size. (b) At Facebook, the amount of data for recommendation use cases has roughly doubled between 2019 and 2021, leading to 3.2 times increase in the data ingestion bandwidth demand. (c) Facebook's recommendation and ranking model sizes have increased by 20 times during the same time period. (d) The explosive growth in AI has driven 2.9× and 2.5 × capacity increases for AI training and inference, respectively.

C.-J. Wu et al., "Sustainable ai: Environmental implications, challenges and opportunities," Proceedings of Machine Learning and Systems, vol. 4, pp. 795-813, 2022.

# AI modus operandi

01 **Collecting as much data as possible**

increasing the quantity of training data so that no opportunity is missed

02 **Improving Model Performance**

Accuracy or any related measures

03 **Increasing complexity**

Logarithmic with linear gain in performance

**The Elephant in the Room**

bigger is better

Despite the positive societal benefits, the endless pursuit of achieving higher model quality has led to the exponential scaling of AI with significant energy and environmental footprint implications

# Green AI

# Definitions

**The term Green AI refers to:**

- **AI research that yields novel results while considering the computational cost, encouraging a reduction in resources spent.[1]**
- **Harnessing the full potential of AI without a negative impact in our planet.[2]**

**Red AI refers to AI research that seeks to improve accuracy (or related measures) using massive computational power while disregarding the cost—essentially “buying” stronger results.**


1. R. Schwartz, J. Dodge, N. A. Smith, and O. Etzioni, "Green ai," Communications of the ACM, vol. 63, no. 12, pp. 54-63, 2020.
2. R. Verdecchia, J. Sallou, and L. Cruz, "A Systematic Review of Green AI," arXiv preprint arXiv:2301.11047, 2023.

https://www.bcg.com/publications/2022/how-ai-can-help-climate-change

# AI Is Essential for Solving the Climate Crisis

**87% of climate and AI leaders found AI to be a helpful tool in the fight against climate change, with reducing and measuring emissions cited as the top drivers for creating business value, BCG, July 7, 2022.**

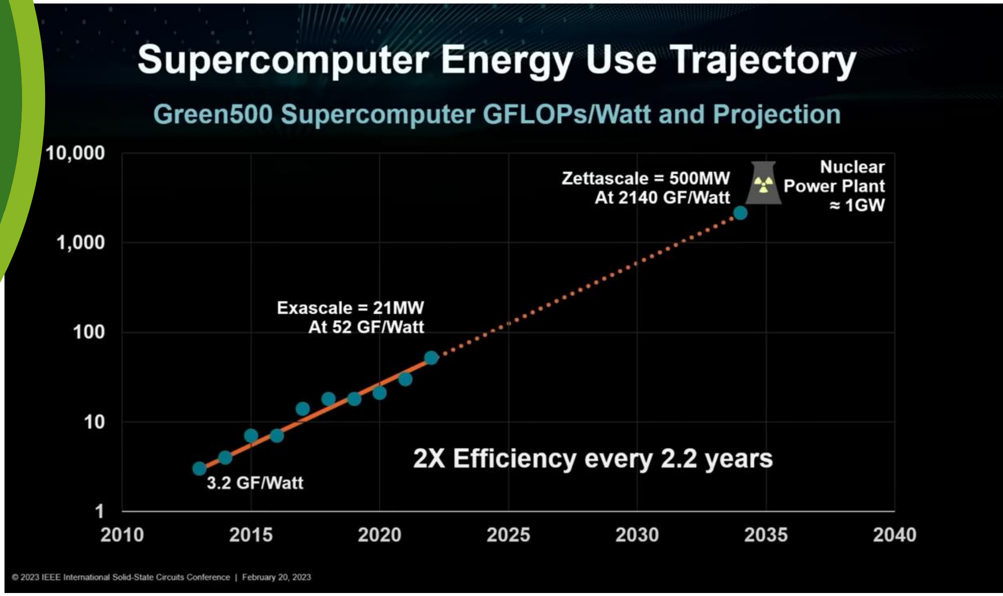
# Controversial statistics

## Training an AI Model can emit / consume

- As much carbon as five cars in their lifetimes.[1]
- Energy equivalent to a trans American flight.[2]
- More than 626,000 pounds of carbon dioxide equivalent.[3]
- More than 500 and 75 metric tons of carbon dioxide, for OpenAI's GPT-3 and Meta's OPT, respectively.[4]
- 300,000 kg of carbon dioxide, which is roughly equivalent to 125 round-trip flights between New York and Beijing. [5]


## Computing

If a zettascale computer were assembled using today's supercomputing technologies, it would consume about 21 gigawatts, or equivalent to the energy produced by 21 nuclear power plants [6].




1. E. Strubell, A. Ganesh, and A. McCallum, "Energy and policy considerations for deep learning in NLP," arXiv preprint arXiv:1906.02243, 2019.
2. E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the dangers of stochastic parrots: Can language models be too big?" Association for Computing Machinery, Inc, 3 2021, pp. 610–623.
3. Green Intelligence: Why Data And AI Must Become More Sustainable, Forbes, March 22, 2023.
4. M. H. page, "We're getting a better idea of AI's true carbon footprint," MIT Technology Review, 2022.
5. P. Dhar, "The carbon impact of artificial intelligence," Nature Machine Intelligence, vol. 2, no. 8, pp. 423--425, 2020
6. Lisa Su, Chair and Chief Executive Officer, AMD, Austin, Texas, Plenary Sessions at IEEE International Solid-State, Feb 20, 2023.

# Suggestions for Tackling AI's Sustainability Impact

## 1
### Environmental impact measures

Tools like Salesforce's Net Zero Cloud, SustainLife, and Microsoft Cloud for Sustainability can help companies visualize and understand their missteps so they can spot opportunities for improvement

## 2
### Estimate carbon footprints of AI models

The Machine Learning Emissions Calculator can help practitioners run estimations based on factors like cloud provider, geographic region, and hardware.

## 3
### Examine how and where data is stored

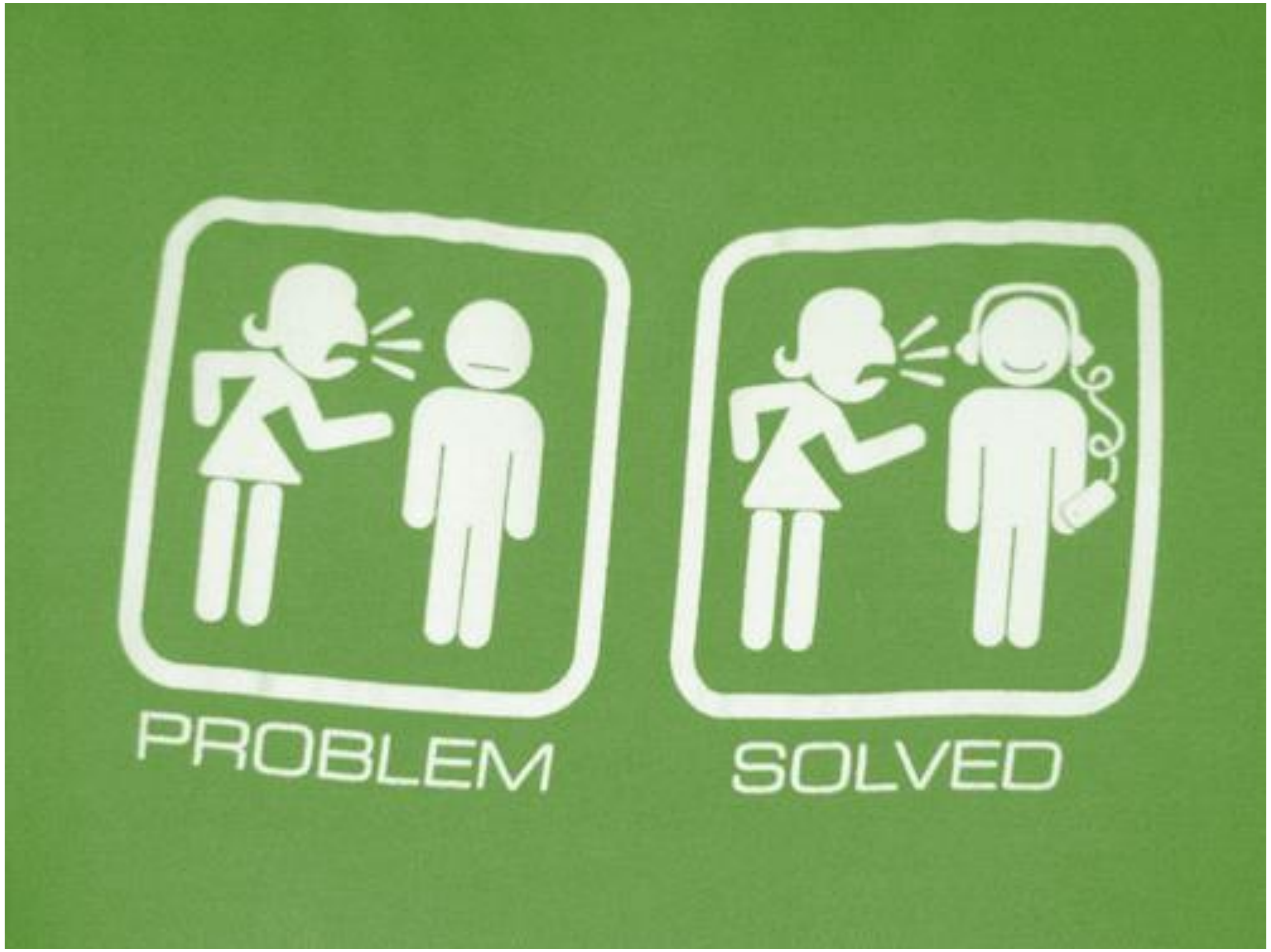
Large machine learning jobs might be moved to more carbon-friendly regions of the world. For example, Montreal, Canada has a number of data centers that run on hydroelectricity.

## 4
### Increase transparency and measurement

Published results should include energy alongside with performance and accuracy metrics

## 5
### Follow Google's "4M" best practices

ML model architectures
Machine
Mechanization
Map Optimization


PROBLEM
SOLVED

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# Research

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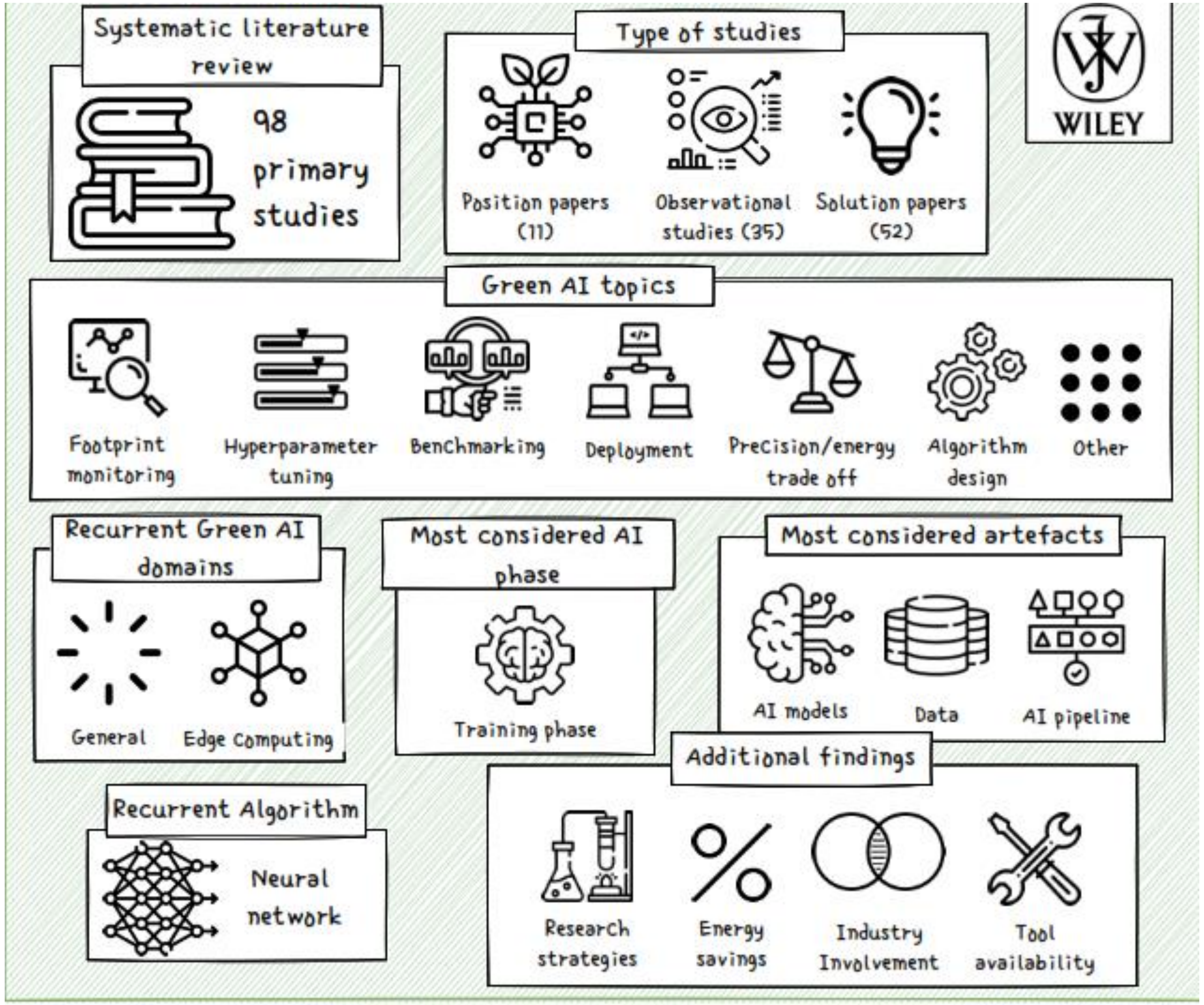
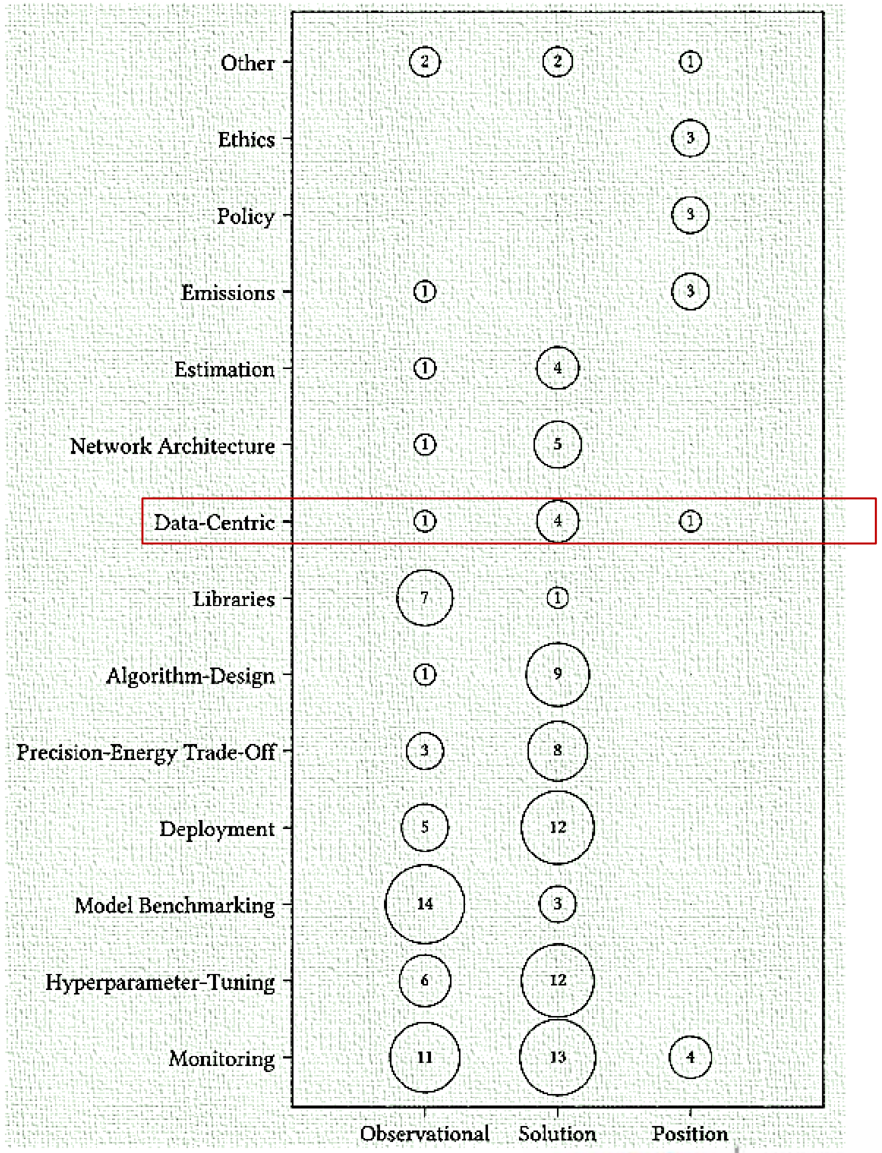
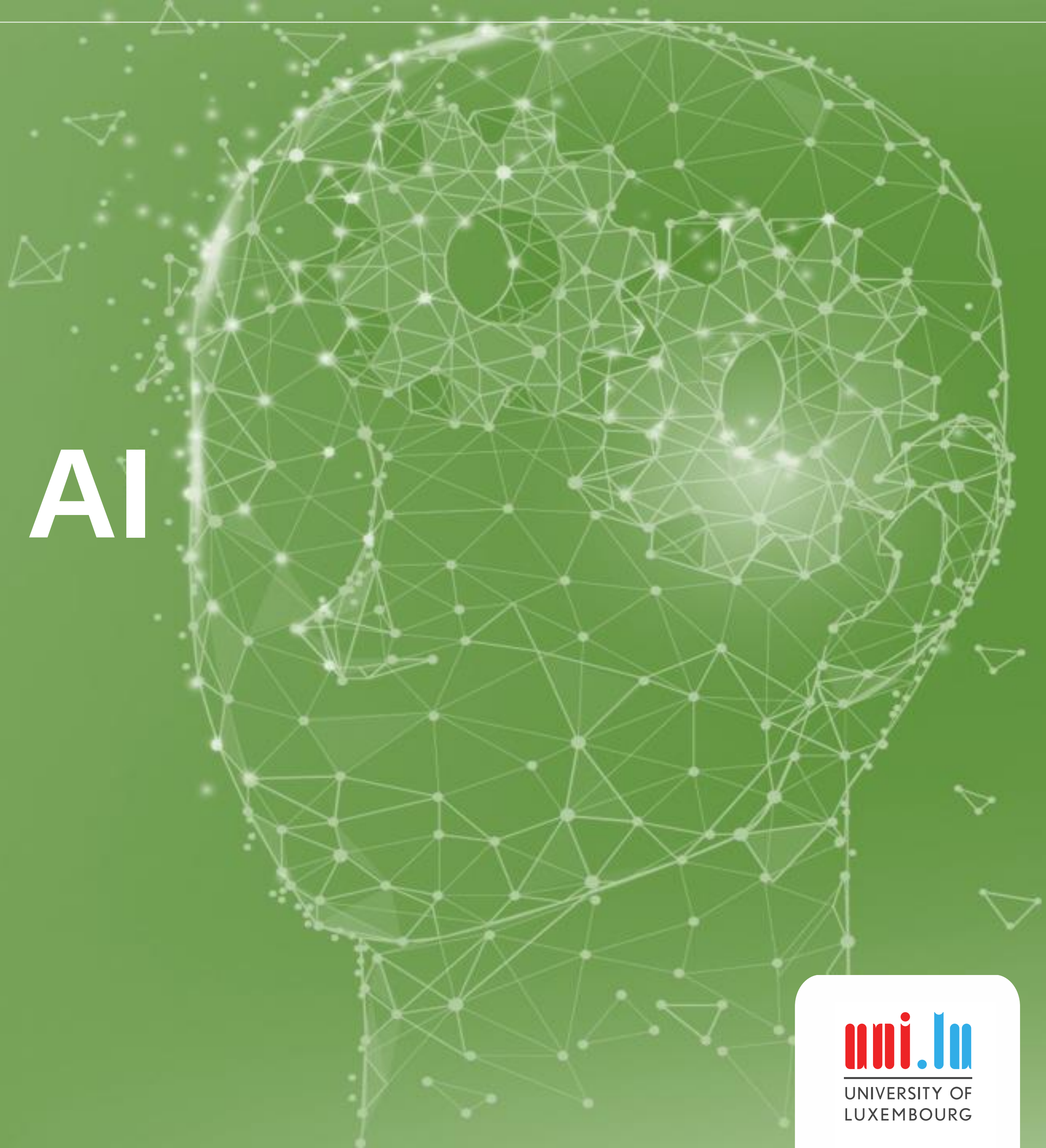
# Systematic Review of Green AI




R. Verdecchia, J. Sallou, and L. Cruz, "A Systematic Review of Green AI," arXiv preprint arXiv:2301.11047, 2023.



# Data-Centric AI

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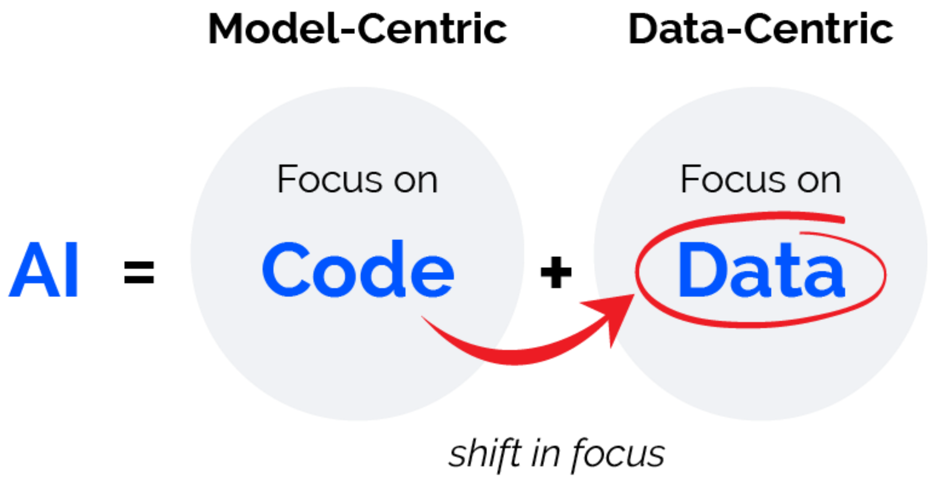
# Think of a Data-Centric AI system as programming with focus on data instead of code

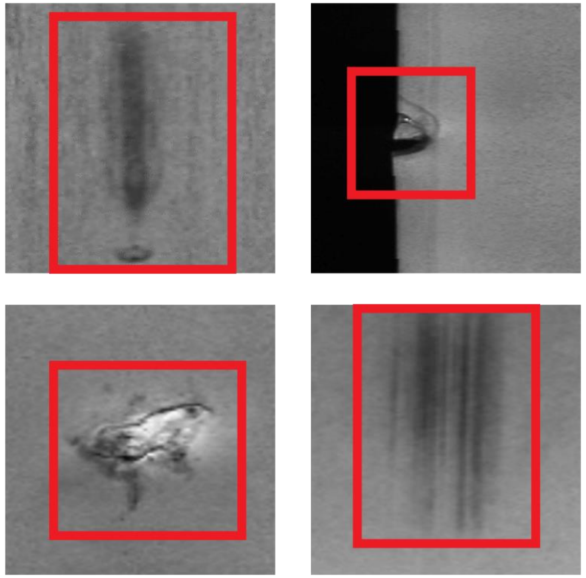
## Why Does Data-Centric AI Matter?

Build computer vision applications 10x faster
Reduced time to deploy application
Improved yield and accuracy

## Data-Centric AI Impacts Performance

A Data-Centric AI approach involves building AI systems with quality data — with a focus on ensuring that the data clearly conveys what the AI must learn. Doing so helps teams reach the performance level required and removes unnecessary trial-and-error time spent on improving the model without changing inconsistent data.



Steel Sheet Defects Example

| *Computer vision task (steel sheet inspection)* | Accuracy |
|---|---|
| Baseline | 76.2% |
| Model-Centric | +0% |
| Data-Centric | +16.9% (93.1%) |

# Can Data-Centric contribute to sustainable AI?

**In recent years, studies have focused on demonstrating how AI energy efficiency can be improved by tuning the model training strategy. Nevertheless, how modifications applied to datasets can impact the energy consumption of AI is still an open question.**

**Interesting Study of Trade-offs between AI energy consumption and accuracy**

- **AI Algorithm ($IV_1$):** `Support-Vector Machine, Decision Tree, Multinomial Naive Bayes, K-Nearest Neighbour, Random Forest, Adaptive Boost, Bagging Classifier.`
- **Number of data points ($IV_2$):** `10%, 20%, 30%, ..., 100%` of the total number of data points. To select data points, we adopt stratified sampling, and pick points of our population uniformly at random from each stratum (i.e., messages labeled as "spam" and "ham").
- **Number of features ($IV_3$):** `10%, 20%, 30%, ..., 100%`

Can we find the minimal data subset to achieve this compromise?

In the vast majority of cases, decreasing the number of data points / features drastically reduces energy consumption, while implying only a negligible accuracy deterioration (e.g., by reducing features, Random Forest can achieve a maximum of 74.81% energy reduction at the cost of only a 0.06% F1-score reduction).

However, this observation does not hold for all algorithms. For example, feature selection when using KNN has almost no impact on energy consumption, while considerably reducing its model performance (with a maximum of 0.92% energy reduction, associated to a 98.05% F1-score loss).

R. Verdecchia, L. Cruz, J. Sallou, M. Lin, J. Wickenden, and E. Hotellier, "Data-centric green ai an exploratory empirical study," in 2022 International Conference on ICT for Sustainability (ICT4S), 2022, pp. 35-45: IEEE.

# Optimisation Problem Alert !

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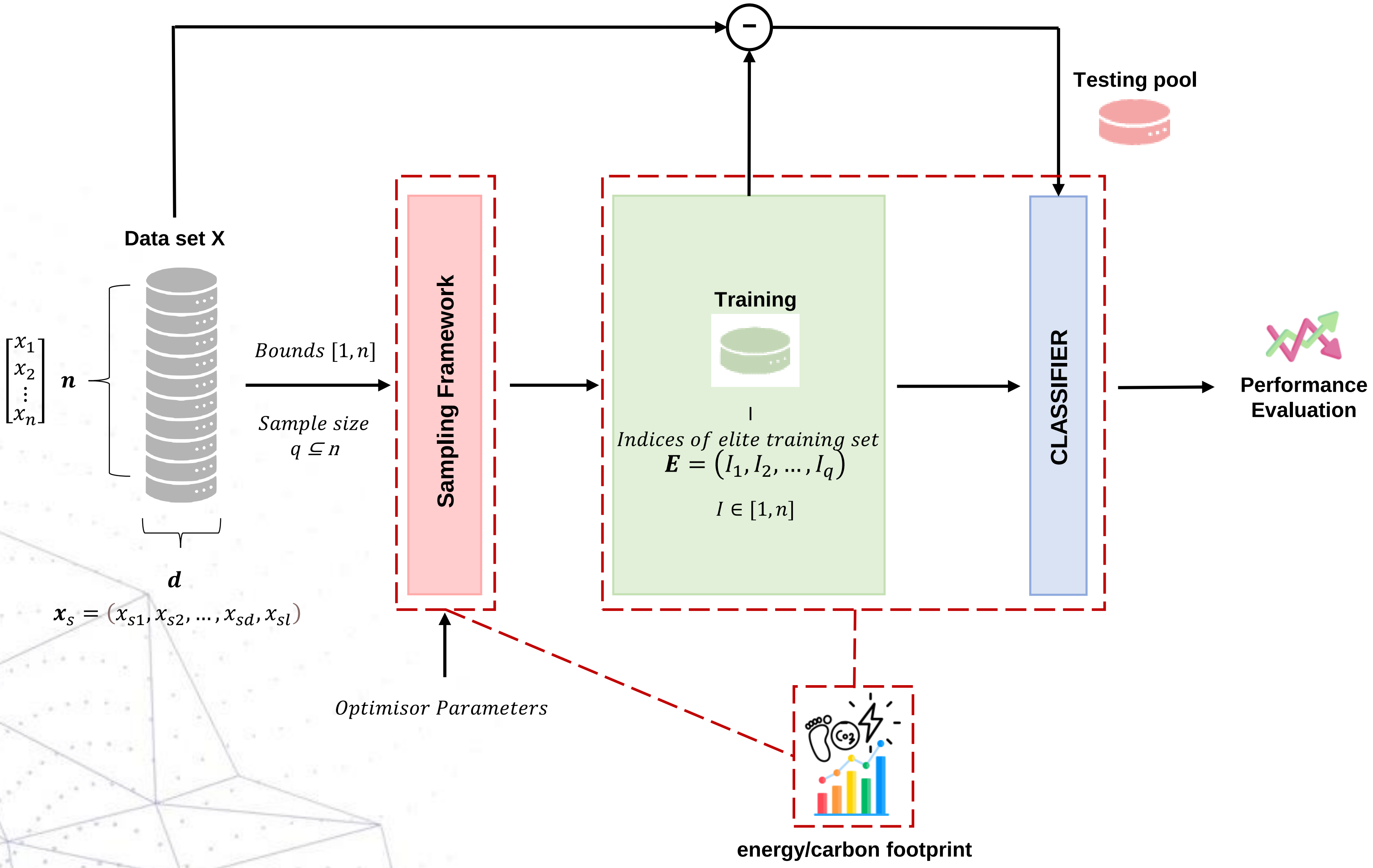
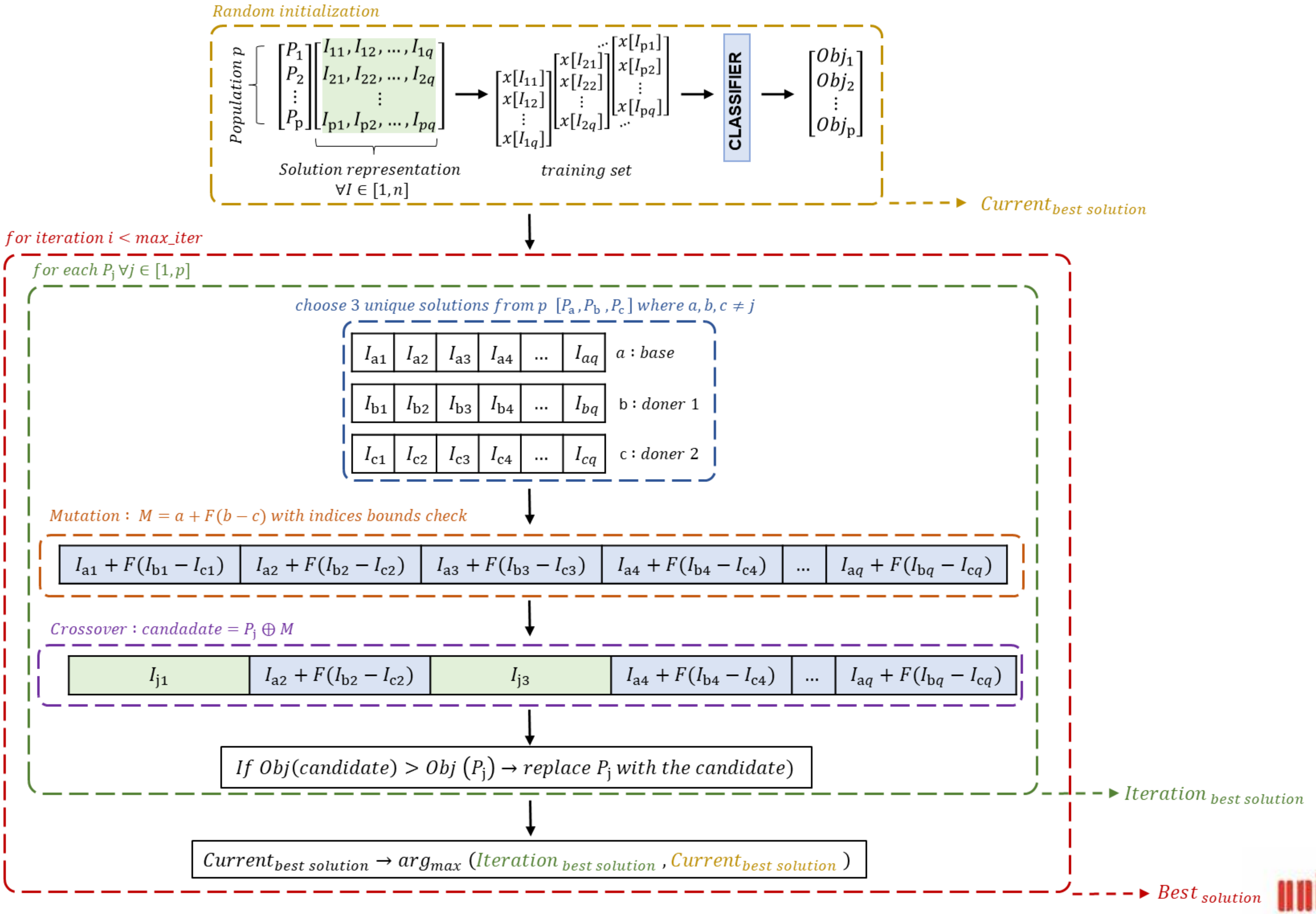
# Elite Data

# Elite Data Sampling Framework



## Sampling Framework based Differential Evolution Optimisation Algorithm



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# Is it worth it?

# Experimental Setup

**Track and reduce CO2 emissions from your computing**

https://github.com/mlco2/codecarbon. Accessed 15th April 2023.

**To mitigate potential threats to the experimentation validity and ensure that all experiments have run under the same hardware conditions,**

- Each experiment has been conducted 30 times and the average of all runs is reported for each evaluation metric.
- The experiment pairs (Classifier, Data set) were randomly shuffled (not 30 runs sequentially) to reduce the effect of unnoticed processes in execution that might affect the energy measurements.
- A 5-second CPU-intensive warm-up operation (before the experiment execution) and 5 seconds sleep interval (between each run) have been introduced to avoid “hardware cold boot” and to enable the hardware to cool down, respectively.
- In each run,—the evaluation metrics—the model classification accuracy, F1-score and training energy consumption in Joules (J) are recorded.

Description of Classification Data Sets

| Dataset | #Obs. | #Atts. | #Cl. | # Hits | Dataset | #Obs. | #Atts. | #Cl. | # Hits |
|---|---|---|---|---|---|---|---|---|---|
| Balance | 625 | 4 | 3 | 339692 | Optdigits | 5620 | 64 | 10 | 393977 |
| Bupa | 345 | 6 | 2 | 235474 | Page-blocks | 5472 | 10 | 5 | 123945 |
| Cleveland | 303 | 13 | 5 | 2221101 | Penbased | 10992 | 16 | 10 | 284812 |
| Coil2000 | 9822 | 85 | 2 | 197453 | Pima | 768 | 8 | 2 | 387040 |
| Contraceptive | 1473 | 9 | 3 | 257663 | Satimage | 6435 | 36 | 7 | 167574 |
| Glass | 214 | 9 | 7 | 476663 | Spambase | 4597 | 57 | 2 | 753397 |
| Haberman | 306 | 3 | 2 | 286064 | Thyroid | 7200 | 21 | 3 | 356055 |
| Heart | 270 | 13 | 2 | 2221151 | Vehicle | 846 | 18 | 4 | 162750 |
| Iris | 150 | 4 | 3 | 5388432 | Wdbc | 569 | 30 | 2 | 2000358 |
| Led7digit | 500 | 7 | 10 | 86507 | Wine | 178 | 13 | 3 | 2194120 |
| Letter | 20000 | 16 | 26 | 493600 | Wisconsin | 699 | 9 | 2 | 289785 |
| Mammographic | 961 | 5 | 2 | 224384 | Yeast | 1484 | 8 | 10 | 376116 |
| Monk-2 | 432 | 6 | 2 | 243363 | | | | | |

https://archive.ics.uci.edu/datasets. Accessed 15th April 2023.
http://www.keel.es. Accessed 15th April 2023.

**Intel(R) Xeon(R) W-2225 CPU @ 4.10GHz equipped with 1 x Quadro RTX 6000 GPU, 128 GB RAM, Linux-5.15.0-53-generic-x86_64-with-glibc2.35 OS, and Python 3.10 .**

**All classifiers used in this study follow the standard implementation with the default parameter settings in the Python package scikit-learn 1.1.2.**

**The sample size is 10% (refereed as reduced training)**

# Experimental Phases

A | Full training (70%) & 30% test | Baseline

B | Reduced training (10%) & 30% test | Fair Comparison

C | Reduced training (10%) & 90% test | Generalizability

# WARNING:

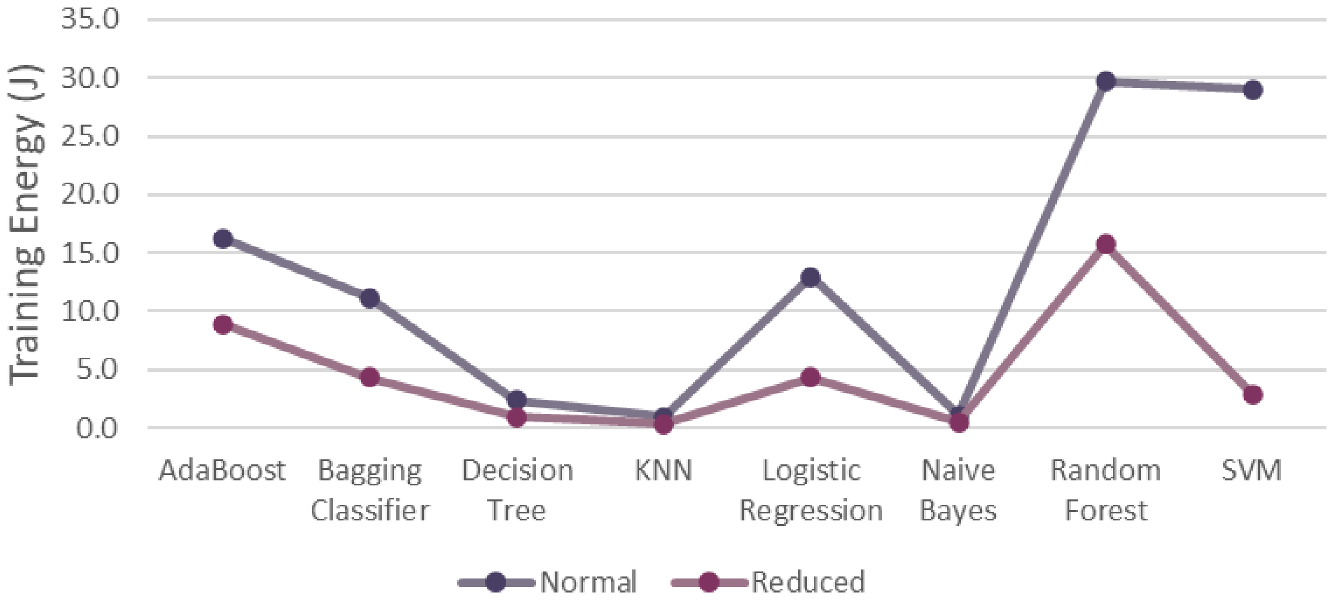
**Viewer Discretion is Advised.**

**ONLY Results of full training and 30% testing data**

# Boring Results sample

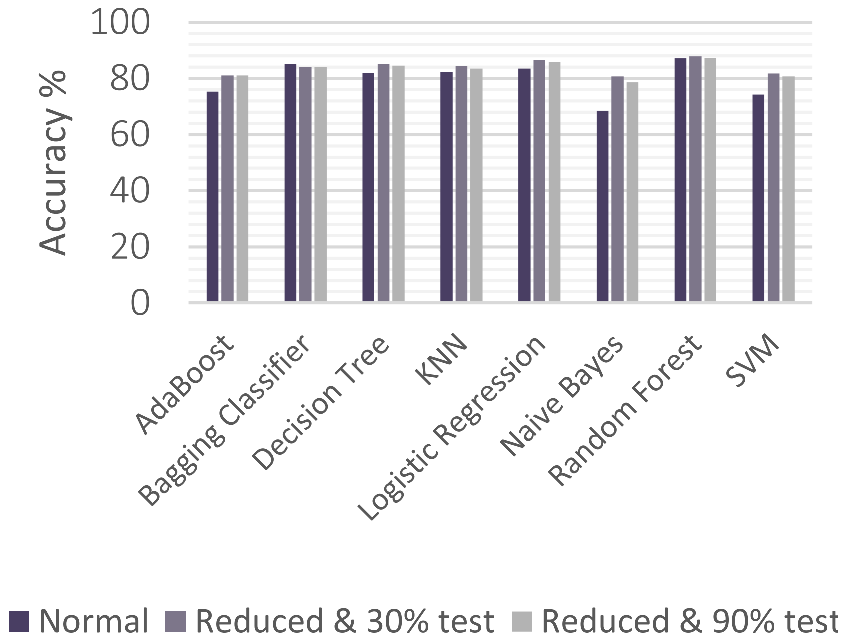
| Dataset | Measure | AdaBoost | | | Bagging Classifier | | | Decision Tree | | | KNN | | | Log_Reg | | | Naive Bayes | | | Random Forest | | | SVM | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE | Acc. | F_Sc. | TE |
| Iris | Mean | 93.78 | 0.94 | 6.23 | 94.59 | 0.95 | 2.56 | 94.81 | 0.95 | 0.68 | 96.67 | 0.97 | 0.62 | 96.52 | 0.97 | 2.30 | 66.67 | 0.55 | 0.69 | 95.48 | 0.95 | 10.52 | 95.48 | 0.95 | 0.73 |
| | SD | 2.88 | 0.03 | 0.18 | 3.18 | 0.03 | 0.40 | 2.50 | 0.03 | 0.04 | 1.62 | 0.02 | 0.02 | 2.08 | 0.02 | 0.23 | 0.00 | 0.00 | 0.04 | 2.30 | 0.02 | 0.28 | 3.38 | 0.03 | 0.02 |
| Tae | Mean | 49.86 | 0.49 | 6.24 | 59.49 | 0.59 | 2.53 | 57.25 | 0.57 | 0.77 | 41.45 | 0.41 | 0.64 | 52.90 | 0.52 | 2.30 | 42.32 | 0.37 | 0.69 | 60.00 | 0.60 | 10.87 | 38.33 | 0.36 | 0.83 |
| | SD | 5.53 | 0.06 | 0.13 | 8.38 | 0.08 | 0.10 | 6.24 | 0.06 | 0.15 | 4.56 | 0.05 | 0.06 | 5.72 | 0.06 | 0.12 | 4.80 | 0.04 | 0.05 | 5.34 | 0.05 | 0.20 | 5.43 | 0.06 | 0.03 |
| Hayes-roth | Mean | 60.42 | 0.56 | 6.26 | 82.71 | 0.86 | 2.51 | 82.71 | 0.85 | 0.72 | 60.76 | 0.60 | 0.65 | 52.36 | 0.55 | 1.47 | 30.42 | 0.27 | 0.71 | 81.60 | 0.85 | 10.81 | 78.82 | 0.82 | 0.84 |
| | SD | 0.00 | 0.00 | 0.15 | 4.31 | 0.04 | 0.08 | 4.28 | 0.04 | 0.06 | 6.99 | 0.08 | 0.06 | 5.89 | 0.06 | 0.11 | 6.82 | 0.07 | 0.02 | 4.55 | 0.04 | 0.16 | 6.05 | 0.06 | 0.02 |
| Wine | Mean | 86.67 | 0.86 | 6.71 | 93.95 | 0.94 | 2.69 | 90.37 | 0.91 | 0.79 | 67.53 | 0.65 | 0.69 | 93.95 | 0.94 | 2.40 | 63.83 | 0.53 | 0.77 | 97.28 | 0.97 | 10.97 | 71.73 | 0.72 | 0.86 |
| | SD | 13.35 | 0.16 | 0.17 | 3.19 | 0.03 | 0.12 | 3.59 | 0.03 | 0.02 | 4.20 | 0.05 | 0.03 | 3.00 | 0.03 | 0.11 | 5.00 | 0.06 | 0.10 | 1.59 | 0.02 | 0.18 | 4.93 | 0.05 | 0.05 |
| Sonar | Mean | 79.63 | 0.79 | 8.92 | 77.25 | 0.77 | 3.80 | 73.44 | 0.73 | 1.24 | 77.14 | 0.76 | 0.72 | 76.46 | 0.76 | 1.36 | 71.16 | 0.71 | 0.77 | 79.89 | 0.79 | 12.47 | 79.37 | 0.79 | 1.01 |
| | SD | 6.13 | 0.06 | 0.22 | 4.61 | 0.05 | 0.15 | 5.67 | 0.06 | 0.05 | 3.58 | 0.04 | 0.08 | 6.45 | 0.06 | 0.14 | 6.04 | 0.06 | 0.02 | 6.46 | 0.07 | 0.26 | 5.42 | 0.06 | 0.06 |
| Glass | Mean | 41.85 | 0.28 | 6.62 | 71.69 | 0.68 | 2.81 | 67.13 | 0.61 | 0.83 | 65.85 | 0.51 | 0.68 | 60.77 | 0.46 | 2.50 | 47.69 | 0.32 | 0.75 | 77.03 | 0.73 | 11.58 | 7.90 | 0.03 | 1.11 |
| | SD | 6.35 | 0.11 | 0.16 | 6.14 | 0.07 | 0.15 | 5.31 | 0.09 | 0.03 | 4.56 | 0.06 | 0.06 | 4.55 | 0.06 | 0.11 | 2.86 | 0.06 | 0.10 | 5.03 | 0.05 | 0.20 | 0.67 | 0.01 | 0.09 |
| Heart | Mean | 79.71 | 0.79 | 6.61 | 79.79 | 0.79 | 2.73 | 73.50 | 0.73 | 0.78 | 67.82 | 0.67 | 0.70 | 84.94 | 0.85 | 2.17 | 74.44 | 0.74 | 0.73 | 82.39 | 0.82 | 11.25 | 69.34 | 0.69 | 0.99 |
| | SD | 3.99 | 0.04 | 0.21 | 3.18 | 0.03 | 0.12 | 5.01 | 0.05 | 0.02 | 5.53 | 0.06 | 0.15 | 3.53 | 0.04 | 0.12 | 3.89 | 0.04 | 0.08 | 4.07 | 0.04 | 0.18 | 5.22 | 0.05 | 0.06 |
| Cleveland | Mean | 51.04 | 0.29 | 6.60 | 54.15 | 0.29 | 2.90 | 48.81 | 0.29 | 0.86 | 49.37 | 0.18 | 0.71 | 57.52 | 0.30 | 2.57 | 53.93 | 0.27 | 0.76 | 57.26 | 0.29 | 11.67 | 38.81 | 0.24 | 1.43 |
| | SD | 5.01 | 0.04 | 0.13 | 4.42 | 0.05 | 0.14 | 4.40 | 0.04 | 0.03 | 3.11 | 0.03 | 0.08 | 3.71 | 0.04 | 0.10 | 2.87 | 0.03 | 0.08 | 2.70 | 0.04 | 0.27 | 6.24 | 0.04 | 0.08 |
| Haberman | Mean | 72.17 | 0.58 | 6.39 | 68.41 | 0.55 | 2.63 | 65.54 | 0.55 | 0.76 | 72.54 | 0.58 | 0.65 | 74.31 | 0.53 | 1.25 | 72.93 | 0.64 | 0.71 | 68.88 | 0.54 | 11.23 | 75.00 | 0.62 | 1.02 |
| | SD | 3.90 | 0.05 | 0.13 | 3.45 | 0.05 | 0.11 | 4.28 | 0.05 | 0.05 | 2.75 | 0.04 | 0.03 | 2.33 | 0.05 | 0.14 | 3.74 | 0.05 | 0.02 | 2.56 | 0.04 | 0.25 | 3.30 | 0.05 | 0.08 |
| Bupa | Mean | 69.87 | 0.69 | 6.43 | 65.16 | 0.64 | 2.76 | 61.41 | 0.61 | 0.82 | 66.35 | 0.64 | 0.68 | 67.34 | 0.65 | 1.63 | 56.19 | 0.56 | 0.75 | 71.47 | 0.70 | 11.63 | 66.92 | 0.67 | 1.09 |
| | SD | 4.66 | 0.05 | 0.14 | 5.10 | 0.05 | 0.11 | 4.50 | 0.05 | 0.02 | 4.40 | 0.05 | 0.02 | 4.44 | 0.04 | 0.13 | 3.51 | 0.04 | 0.06 | 4.11 | 0.04 | 0.44 | 4.10 | 0.04 | 0.05 |
| Movement-libras | Mean | 13.30 | 0.06 | 2.80 | 70.49 | 0.70 | 2.89 | 65.40 | 0.65 | 3.87 | 69.63 | 0.69 | 4.08 | 65.31 | 0.64 | 3.09 | 41.36 | 0.33 | 1.99 | 78.95 | 0.79 | 2.90 | 77.69 | 0.77 | 2.87 |
| | SD | 2.14 | 0.02 | 3.03 | 4.19 | 0.04 | 3.84 | 4.59 | 0.05 | 3.90 | 3.84 | 0.04 | 4.20 | 4.02 | 0.04 | 3.70 | 2.80 | 0.03 | 2.73 | 3.00 | 0.03 | 3.51 | 3.18 | 0.03 | 3.33 |
| Dermatology | Mean | 62.31 | 0.44 | 6.84 | 96.20 | 0.95 | 2.86 | 94.57 | 0.93 | 0.84 | 85.52 | 0.83 | 0.67 | 97.16 | 0.97 | 2.81 | 89.97 | 0.87 | 0.78 | 97.16 | 0.97 | 11.29 | 70.25 | 0.64 | 1.53 |
| | SD | 13.92 | 0.17 | 0.15 | 1.73 | 0.03 | 0.38 | 1.53 | 0.02 | 0.03 | 2.84 | 0.03 | 0.02 | 1.29 | 0.01 | 0.12 | 3.02 | 0.04 | 0.10 | 1.26 | 0.02 | 1.12 | 3.60 | 0.05 | 0.07 |
| Monk-2 | Mean | 100.00 | 1.00 | 6.42 | 100.00 | 1.00 | 2.54 | 100.00 | 1.00 | 0.75 | 98.46 | 0.98 | 0.67 | 76.62 | 0.76 | 1.18 | 74.97 | 0.75 | 0.74 | 99.28 | 0.99 | 11.13 | 97.64 | 0.98 | 1.05 |
| | SD | 0.00 | 0.00 | 0.15 | 0.00 | 0.00 | 0.10 | 0.00 | 0.00 | 0.10 | 1.14 | 0.01 | 0.04 | 2.85 | 0.03 | 0.07 | 2.86 | 0.03 | 0.09 | 1.05 | 0.01 | 0.35 | 1.38 | 0.01 | 0.05 |
| Led7digit | Mean | 61.02 | 0.58 | 6.65 | 70.64 | 0.71 | 2.64 | 69.58 | 0.69 | 0.78 | 69.53 | 0.69 | 0.70 | 74.27 | 0.74 | 2.40 | 61.49 | 0.53 | 0.76 | 70.73 | 0.70 | 11.23 | 72.76 | 0.73 | 1.48 |
| | SD | 8.73 | 0.11 | 0.14 | 3.79 | 0.04 | 0.13 | 3.04 | 0.03 | 0.02 | 3.21 | 0.04 | 0.03 | 2.61 | 0.03 | 0.11 | 2.44 | 0.03 | 0.06 | 2.99 | 0.03 | 0.21 | 3.18 | 0.03 | 0.07 |
| Bands | Mean | 67.15 | 0.64 | 6.85 | 67.12 | 0.65 | 3.18 | 63.27 | 0.61 | 0.98 | 61.45 | 0.56 | 0.66 | 67.55 | 0.61 | 2.16 | 59.15 | 0.58 | 0.76 | 72.12 | 0.67 | 12.15 | 55.76 | 0.56 | 1.20 |
| | SD | 4.39 | 0.05 | 0.16 | 4.05 | 0.04 | 0.13 | 3.82 | 0.04 | 0.04 | 4.29 | 0.05 | 0.02 | 3.97 | 0.05 | 0.20 | 3.85 | 0.04 | 0.04 | 3.21 | 0.05 | 0.19 | 3.82 | 0.04 | 0.06 |
| Wdbc | Mean | 95.85 | 0.96 | 9.85 | 94.35 | 0.94 | 4.22 | 93.04 | 0.93 | 1.36 | 92.87 | 0.92 | 0.68 | 94.15 | 0.94 | 3.40 | 89.14 | 0.88 | 0.77 | 96.35 | 0.96 | 13.92 | 90.58 | 0.90 | 1.26 |
| | SD | 1.39 | 0.02 | 0.17 | 1.71 | 0.02 | 0.18 | 1.97 | 0.02 | 0.12 | 1.87 | 0.02 | 0.06 | 1.57 | 0.02 | 0.25 | 1.87 | 0.02 | 0.05 | 1.64 | 0.02 | 0.24 | 2.05 | 0.02 | 0.07 |
| Balance | Mean | 91.29 | 0.82 | 6.53 | 80.11 | 0.59 | 2.67 | 77.85 | 0.58 | 0.76 | 83.46 | 0.61 | 0.67 | 87.38 | 0.63 | 1.77 | 87.23 | 0.61 | 0.71 | 84.59 | 0.60 | 11.73 | 82.34 | 0.75 | 1.41 |
| | SD | 2.31 | 0.05 | 0.12 | 2.39 | 0.01 | 0.10 | 1.98 | 0.02 | 0.02 | 1.79 | 0.03 | 0.03 | 1.19 | 0.04 | 0.14 | 1.38 | 0.01 | 0.01 | 1.80 | 0.01 | 0.81 | 2.64 | 0.03 | 0.06 |
| Wisconsin | Mean | 95.87 | 0.95 | 6.69 | 96.08 | 0.96 | 2.68 | 94.42 | 0.94 | 0.79 | 96.78 | 0.96 | 0.69 | 96.62 | 0.96 | 1.42 | 85.22 | 0.84 | 0.72 | 96.85 | 0.97 | 11.25 | 96.98 | 0.97 | 1.00 |
| | SD | 1.02 | 0.01 | 0.14 | 1.33 | 0.01 | 0.09 | 1.97 | 0.02 | 0.03 | 1.05 | 0.01 | 0.02 | 0.94 | 0.01 | 0.08 | 2.25 | 0.02 | 0.02 | 1.06 | 0.01 | 0.19 | 1.07 | 0.01 | 0.05 |
| Pima | Mean | 74.62 | 0.71 | 7.46 | 74.56 | 0.72 | 3.49 | 70.48 | 0.67 | 1.08 | 72.24 | 0.69 | 0.74 | 76.46 | 0.72 | 2.32 | 58.37 | 0.55 | 0.79 | 75.24 | 0.71 | 13.83 | 72.63 | 0.71 | 1.93 |
| | SD | 1.94 | 0.02 | 0.16 | 2.72 | 0.03 | 0.11 | 3.20 | 0.04 | 0.07 | 2.43 | 0.03 | 0.02 | 2.99 | 0.04 | 0.09 | 2.32 | 0.03 | 0.08 | 1.83 | 0.02 | 0.29 | 2.32 | 0.02 | 0.09 |
| Vehicle | Mean | 58.20 | 0.60 | 8.73 | 73.27 | 0.73 | 4.43 | 69.17 | 0.69 | 1.40 | 63.31 | 0.62 | 0.68 | 71.13 | 0.71 | 3.20 | 39.37 | 0.29 | 0.79 | 74.99 | 0.74 | 16.37 | 45.92 | 0.44 | 2.78 |
| | SD | 3.84 | 0.04 | 0.88 | 2.11 | 0.02 | 0.14 | 2.32 | 0.02 | 0.08 | 2.25 | 0.02 | 0.02 | 2.54 | 0.03 | 0.38 | 1.83 | 0.03 | 0.07 | 2.33 | 0.02 | 0.27 | 2.55 | 0.03 | 0.13 |
| Mammographic | Mean | 82.25 | 0.82 | 6.85 | 78.45 | 0.78 | 2.88 | 76.61 | 0.77 | 0.87 | 80.25 | 0.80 | 0.73 | 83.11 | 0.83 | 1.91 | 76.44 | 0.76 | 0.77 | 78.76 | 0.79 | 12.53 | 77.15 | 0.77 | 1.96 |
| | SD | 2.03 | 0.02 | 0.13 | 2.04 | 0.02 | 0.14 | 2.25 | 0.02 | 0.08 | 2.56 | 0.03 | 0.08 | 2.09 | 0.02 | 0.18 | 2.25 | 0.02 | 0.06 | 1.73 | 0.02 | 0.20 | 2.05 | 0.02 | 0.12 |

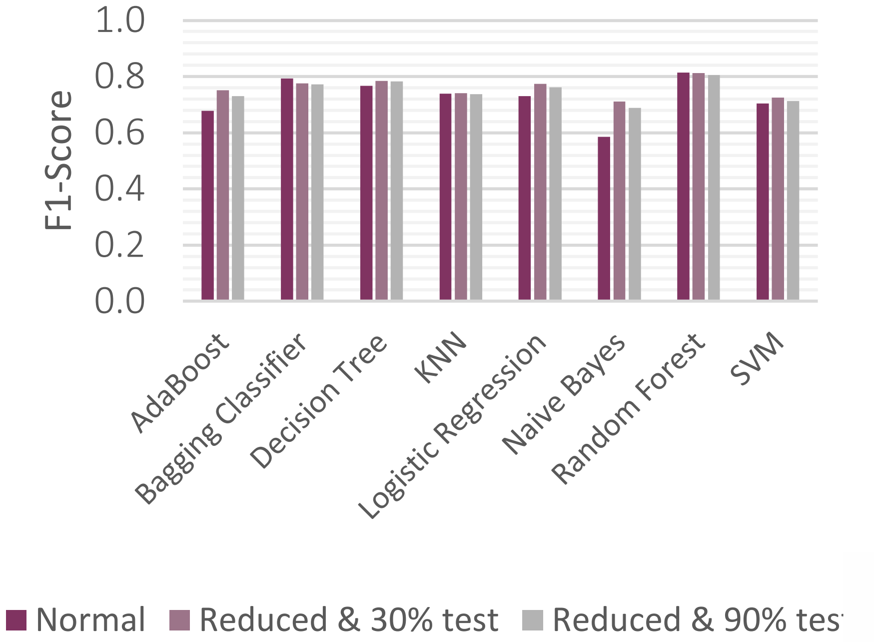
# Overall performance




Overall Average Training Energy Consumption of Classifiers over all datasets

Overall Average Classification Accuracy and F1- Score of Classifiers over all datasets



# Deeper Look into Results

Average Accuracy with reduced training and 30% test sets

| | AdaBoost | Bagging Classifier | Decision Tree | KNN | Logistic Regression | Naive Bayes | Random Forest | SVM |
|---|---|---|---|---|---|---|---|---|
| Balance | -5% | 1% | 3% | 3% | 5% | 3% | 0% | 6% |
| Bupa | 4% | -2% | 7% | 7% | 7% | 16% | -1% | 6% |
| Cleveland | 1% | 3% | 9% | 8% | 6% | 10% | 3% | 19% |
| Coil2000 | 0% | 1% | 2% | 1% | 0% | 14% | 2% | 17% |
| Contraceptive | 2% | 2% | 4% | 3% | 4% | 4% | 2% | 3% |
| Glass | 23% | -9% | 3% | 3% | 5% | 18% | -4% | 54% |
| Haberman | 5% | 7% | 13% | 7% | 5% | 7% | 8% | 4% |
| Heart | 6% | 0% | 12% | 6% | 2% | 11% | 3% | 7% |
| Iris | 2% | 2% | 4% | 3% | 3% | 28% | 2% | 4% |
| Led7digit | 6% | -1% | 3% | 7% | 1% | 11% | 2% | 3% |
| Letter | -3% | -6% | -7% | -7% | 0% | 5% | -4% | -5% |
| Mammographic | 3% | 5% | 8% | 0% | 3% | 4% | 6% | -2% |
| Monk-2 | 0% | 0% | 0% | -2% | 12% | 5% | 0% | 2% |
| Optdigits | 11% | -1% | -3% | 0% | 0% | 5% | -1% | 0% |
| Page-blocks | 6% | 0% | 1% | 0% | 2% | 2% | 0% | 12% |
| Penbased | 36% | -1% | -2% | 0% | 0% | 28% | 0% | 0% |
| Pima | 3% | 0% | 6% | 2% | 3% | 12% | 3% | 4% |
| Satimage | 10% | -2% | 0% | -1% | 1% | 7% | -1% | 0% |
| Spambase | 0% | -1% | 0% | -3% | 1% | 10% | -1% | 2% |
| Thyroid | 0% | 0% | 0% | 0% | 0% | 36% | 0% | 26% |
| Vehicle | 7% | -5% | 1% | -4% | 3% | 14% | -1% | 2% |
| Wdbc | -1% | -1% | 2% | 2% | 2% | 3% | 1% | 3% |
| Wine | 10% | -8% | 3% | 11% | 0% | 30% | 0% | 7% |
| Wisconsin | 2% | 0% | 3% | 2% | 1% | 5% | 1% | 1% |
| Yeast | 14% | -1% | 4% | 0% | -1% | 7% | -3% | 1% |

-10%
0
60%

# Deeper Look into Results - Generalizability

Average Accuracy with reduced training and 90% test sets

| | AdaBoost | Bagging Classifier | Decision Tree | KNN | Logistic Regression | Naive Bayes | Random Forest | SVM |
|---|---|---|---|---|---|---|---|---|
| Balance | -4% | -1% | 2% | 3% | 4% | 3% | 0% | 6% |
| Bupa | 2% | 1% | 8% | 4% | 6% | 15% | -2% | 3% |
| Cleveland | 8% | 3% | 11% | 7% | 4% | 7% | 4% | 17% |
| Coil2000 | 0% | 1% | 2% | 1% | 0% | 11% | 1% | 15% |
| Contraceptive | 1% | 2% | 5% | 2% | 3% | 3% | 2% | 2% |
| Glass | 22% | -10% | 2% | -1% | 4% | 15% | -7% | 49% |
| Haberman | 5% | 5% | 11% | 6% | 4% | 5% | 7% | 3% |
| Heart | 5% | 0% | 9% | 4% | 1% | 10% | 2% | 3% |
| Iris | 3% | -1% | 3% | 2% | 3% | 26% | 1% | 3% |
| Led7digit | -2% | -2% | 2% | 5% | 0% | 8% | 2% | 1% |
| Letter | 7% | -7% | -8% | -7% | 0% | 5% | -5% | -5% |
| Mammographic | 2% | 5% | 7% | 0% | 2% | 3% | 5% | -3% |
| Monk-2 | 0% | -1% | 0% | -4% | 11% | 3% | 0% | 1% |
| Optdigits | 9% | -1% | -3% | 0% | 0% | 4% | -1% | 0% |
| Page-blocks | 6% | 0% | 1% | 0% | 1% | 2% | 0% | 10% |
| Penbased | 34% | -1% | -2% | 0% | 0% | 10% | 0% | 0% |
| Pima | 2% | -1% | 5% | 3% | 2% | 11% | 1% | 3% |
| Satimage | 13% | -1% | -1% | -1% | 1% | 6% | -1% | 0% |
| Spambase | 0% | -1% | 0% | -3% | 1% | 9% | -1% | 1% |
| Thyroid | 0% | 0% | 0% | 0% | 0% | 35% | 0% | 23% |
| Vehicle | 6% | -5% | 0% | -4% | 1% | 11% | -3% | 2% |
| Wdbc | 1% | -1% | 2% | 2% | 2% | 3% | 1% | 3% |
| Wine | 7% | -3% | 1% | 9% | 3% | 29% | 0% | 5% |
| Wisconsin | 2% | 0% | 2% | 1% | 1% | 4% | 1% | 1% |
| Yeast | 12% | -2% | 3% | 0% | -2% | 6% | -3% | 0% |

-10%
0
60%

# Deeper Look into Results – More Ecofriendly AI models

Training energy reduction percentage including the optimiser

| | AdaBoost | Bagging Classifier | Decision Tree | KNN | Logistic Regression | Naive Bayes | Random Forest | SVM |
|---|---|---|---|---|---|---|---|---|
| Balance | 9% | 14% | 50% | 52% | 27% | 47% | 11% | 70% |
| Bupa | 7% | 15% | 52% | 49% | 17% | 48% | 10% | 61% |
| Cleveland | 10% | 20% | 57% | 56% | 20% | 50% | 12% | 71% |
| Coil2000 | 72% | 86% | 79% | 48% | 67% | 71% | 74% | 98% |
| Contraceptive | 14% | 27% | 59% | 53% | 29% | 47% | 27% | 85% |
| Glass | 5% | 4% | 39% | 31% | 3% | 29% | 3% | 50% |
| Haberman | 8% | 14% | 52% | 48% | 27% | 48% | 9% | 61% |
| Heart | 11% | 16% | 51% | 54% | 15% | 47% | 10% | 60% |
| Iris | 6% | 9% | 46% | 50% | 32% | 47% | 4% | 48% |
| Led7digit | 7% | 10% | 48% | 47% | 39% | 46% | 4% | 66% |
| Letter | 67% | 67% | 57% | 37% | 73% | 72% | 64% | 82% |
| Mammographic | 12% | 16% | 57% | 57% | 24% | 52% | 16% | 76% |
| Monk-2 | 7% | 8% | 46% | 54% | 29% | 48% | 5% | 60% |
| Optdigits | 52% | 65% | 52% | 54% | 76% | 54% | 52% | 69% |
| Page-blocks | 40% | 62% | 53% | 44% | 40% | 51% | 49% | 91% |
| Penbased | 57% | 67% | 57% | 37% | 84% | 65% | 61% | 73% |
| Pima | 17% | 30% | 62% | 54% | 21% | 49% | 23% | 76% |
| Satimage | 55% | 69% | 59% | 30% | 53% | 55% | 60% | 79% |
| Spambase | 48% | 72% | 59% | 61% | 32% | 54% | 52% | 90% |
| Thyroid | 49% | 32% | 62% | 55% | 67% | 58% | 43% | 96% |
| Vehicle | 26% | 43% | 65% | 43% | 31% | 47% | 29% | 61% |
| Wdbc | 35% | 39% | 70% | 56% | 42% | 51% | 25% | 67% |
| Wine | 12% | 16% | 52% | 56% | 14% | 52% | 7% | 55% |
| Wisconsin | 1% | 1% | 37% | 30% | 21% | 37% | 2% | 46% |
| Yeast | 26% | 41% | 67% | 61% | 60% | 53% | 39% | 85% |

0%
50%
100%

# Conclusion & Future Work

**Data-centric Green AI demonstrates very high potential to address the sustainability of AI-based software-intensive systems. Learn from less data is both economical and eco-friendly.**

- **Better Understanding of the relation between Model and data**

  Why elite data is different for each model?
  Can we find the ultimate subset that works for all models?
  .
  .
  .

- **Dynamic sample size for each model and data set pairs**

- **Community effort (Green AI data repository)**

SnT

## Parallel Computing and Optimisation Group

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# Thanks for watching

## ANY QUESTIONS?