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Green AI Practices in Multi-objective Hyperparameter Optimization for Sustainable Machine Learning

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Abstract: The hyperparameter tuning process is an essential step for ML model optimization, as it is necessary to improve model performance. However, this enhancement involves high computational resources and time costs. Model tuning can significantly raise energy consumption and consequently increase carbon emissions. Therefore, there is an essential need to construct a new framework for this challenge by adding carbon emissions as a vital consideration along with performance. The paper proposes a novel Sustainable Hyperparameter Optimization (SHPO) framework that uses an optimized multi-objective fitness approach. The framework focuses on ensemble classification models (ECMs) namely, Random Forest, ExtraTrees, XGBoost, and AdaBoost. All these models will be optimized using traditional and advanced techniques like Optuna, Hyperopt, and Grid Search. The proposed framework tracks carbon emissions during model hyperparameter tuning. The methodology uses the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as a method of multi-criteria decision-making (MCDM). This TOPSIS method ranks the hyperparameter sets based on both accuracy and carbon emissions. The objective of the multi-objective fitness approach is to reach the best parameter set with high accuracy and low carbon emissions. It is observed from the experimental results that Optuna based Hyperparameter optimization consistently produced low carbon emissions and achieved high predictive accuracy across the majority of benchmark hyperparameter setups for the models.

Index Terms: Green AI, Sustainable Environment, Multi Objective Fitness, Machine Learning, Hyperparameter Optimization.

1. Introduction

Machine Learning (ML) has quickly grown in prominence and is now applied across various sectors for accurate forecasting and task automation. It analyzes vast quantities of and produces precise insights enhancing efficiency and accuracy in processes [1]. However, the increasing application of ML has resulted in greater computational requirements. Deciding the optimal set of hyperparameters to increase the performance which is the main crucial aspect of establishing ML applications [2]. At the same time complexity of hyperparameter in ensemble ML models directly affects the computational resources required. Computational resources regarding time and processing power are necessary to fine-tune these hyperparameters [3]. All ensemble models with No of Estimators which is known as no of trees. The maximum no of trees significantly increasing the computational time and resources. For example, all ensemble models with 500 trees requires more computation than 100 trees. This directly increase the CPU/GPU runtime (utilization). Maximum depth and minimum samples split are the parameters of the ensemble models. These parameters control the complexity of each tree. Larger and deeper decision trees take more time to build and evaluate at training the model. Low learning rate also extends the training time. There for increased training cycles takes their own time with respect to the complexity. This larger training time and high resource utilization consumes more energy. High energy leading to higher carbon emissions. Such emissions are detrimental to the environment as they contribute to global warming and climate change. As ML models grow more intricate during hyperparameter tuning, the need for computational power during Hyperparameter Optimization (HPO) escalates, resulting in a larger environmental footprint. The energy consumed by computers while training models emits carbon dioxide (CO_2) and other greenhouse gases [4], negatively impacting the environment, human health, and natural resources. With an increasing awareness of climate issues, "Green AI" has gained traction. Green AI aims to minimize the ecological footprint of ML [5], particularly by reducing carbon emissions during the training and optimization phases. It encompasses two main domains [6]: algorithm optimization and hardware optimization. Algorithm optimization involves creating and refining algorithms to ensure high performance while minimizing energy use and carbon output. Hardware optimization focuses on enhancing the energy efficiency of the computing devices utilized. This shift in perspective necessitates new methods for developing ML models, where sustainability is prioritized alongside conventional performance criteria [7].

Traditional approaches in hyperparameter optimization (HPO) mainly concentrate on attaining high accuracy by ignoring environmental indications. This research paper undertakes this gap by examining both emission and accuracy in HPO. It contributes a novel approach designated as the Sustainable Hyperparameter Optimization (SHPO) framework. This framework holds a multi-objective fitness plan that includes carbon emission and accuracy by adjusting hyperparameters. The SHPO framework includes the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) which is a multi-criteria decision making [8] method to assess and rank the hyperparameters based on their perfection and carbon output. The core of this framework is upgrading numerous Ensemble Classification Models (ECMs) like Random Forest, Extra Trees and Ada Boost. The ensemble model blends the predictions of multiple models to strengthen overall performance. EMCs are specifically effective for developing reliable and precise machine learning applications as they assist in lightening the boundary line of the individual models. All these models are refined by using both traditional and advanced optimization techniques including Optuna, Hyperopt and Grid Search. This framework gives a practical solution for attaining precise machine learning models and acknowledging their environmental footprint.

1.1. Motivation

Computational power is used more by the ML models which uplifts concerns about their environmental sustainability because of carbon emissions. Traditional hyperparameter optimization concentrates on performance metrics namely accuracy with high sustainability. The up-to-date awareness of environmentally responsible AI is inspiring to construct a framework that can detect a significant balance between model performance and minimized carbon footprint. This paper approaches this by engaging in algorithmic optimization for sustainable ML trails.

1.2. Objectives

The key contribution of the proposed framework is to provide an integrated multi objective fitness for optimizing ensemble classification model hyperparameters.

- To develop a framework that can optimize multiple objective fitness simultaneously by focusing on the maximum predictive accuracy while minimizing the carbon emissions associated with training the models.
- To achieve multiple objective fitness, a TOPSIS as an MCDM method is integrated in the proposed framework to effectively balance environmental sustainability and performance metrics in hyperparameter optimization.

1.3. Contributions

- Introduces a SHPO framework that embeds carbon emission tracking and multi objective fitness to balance model accuracy with carbon emission.
- Utilizes the TOPSIS as an MCDM method to rank and select optimal hyperparameter sets to ensure a sustainability to model optimization.
- Suggest a good optimization technique that continuously provides lower carbon emissions along with high model accuracy for Green AI.

The rest of the paper is organized as follows: Section 2 summarizes results from previous work and techniques related to hyperparameter tuning. Section 3 further elucidates the conceptual framework and, by extension, the methodology that is going to be used in the study of the paper. The last section, 4, is devoted to further discussion on the proposed framework's results. Hence, Section 5 concludes with the following summary of the proposed framework outcomes.

2. Review Literature

This section examines the existing relevant methodologies in detail and highlights the strengths and weaknesses of current approaches. Finally, it discusses the identified research gap.

Strubell et al. (2020) [9] study the environmental impacts of AI and, more concretely, carbon emissions produced by training large-scale ML models. The research underlines that model training and optimization of hyperparameters produce a huge footprint in terms of carbon emissions and calls for environmentally friendly attitudes within the framework of AI research. It emphasizes the need to consider carbon monitoring as part of the AI pipeline in order to reduce environmental impact and is espoused by the current study. Bergstra et al. (2011) [10] give an overall review of methodologies related to hyperparameter optimization like Grid Search (GS), Random Search (RS), and Bayesian

Optimization (BO). The efficiency and effectiveness of the different methods on machine learning tasks, in terms of usage of computational resources versus model performance, are discussed. It also looks into recent advances in optimization strategies to alleviate computational complexities. Reference Zopounidis and Doumpos 2018 [11], Review of MCDM techniques in the context of machine learning with a focus on conflicting objectives. Some of the known methods in MCDM are presented: TOPSIS, AHP, PROMETHEE, and their applications to optimize machine learning models. This research indicates that MCDM is a suitable technique for model performance as a balance between computational costs.

Schwartz et al., (2020) [12] They provide a review of sustainable AI practices and propose a framework for taking environmental considerations into account while developing AI. This work also presents some tools and techniques to measure the carbon footprint of AI models and reduce it, for instance through the development of energy-efficient algorithms, carbon-aware scheduling. It discusses different stages of integrating sustainability into the whole value chain of AI lifecycle. Dietterich (2000) [13] gives an excellent review of ensemble methods to be used for classification: bagging, boosting, and stacking. This paper has explained how these methods combine multiple base classifiers to achieve better predictive accuracy and has discussed how hyper-parameters are affecting the performance of an ensemble model. Also, some of the computational complexities associated with the training of the ensemble models were touched on. Thompson et al. (2021) [14] explore current approaches to making machine learning more energy-efficient. It discusses several approaches, such as pruning, quantization, and energy-aware NAS, trying to reduce the energy consumption of a machine learning model with minimal loss in performance. Gao et al. (2021) [15] review carbon-aware scheduling techniques that adaptively adjust the AI workload according to dynamic low-carbon energy source availability. The study shows how these can be integrated into AI systems to reduce their carbon footprint without necessarily sacrificing performance.

Snoek et al. (2012) [16] review Bayesian optimization as a powerful tool for hyperparameter tuning in machine learning. Efficiency in exploring large hyperparameter spaces, along with reducing computational cost due to model training, is discussed. Extensions of Bayesian optimization in recent times for sustainability are also discussed. In Hwang and Yoon (1981) [17], the authors have provided an extensive review of the most widely used MCDM method known as TOPSIS and its applications on various domains. The paper outlines the mathematical basis of TOPSIS and discusses the advantages in ranking alternatives based on multi-criteria. Van Wynsberghe (2021) [18] overviews the ethical and practical issues of sustainable AI. It points out the counterbalancing between technological progress and ecological accountability. The paper discusses the chances for embedding sustainability into AI, from policy recommendations to technical novelties.

It is clear from the review of related works that most of the methodologies either improve the performance of the model or reduce computation costs not both. This creates a literature gap where there is a lack of approaches that integrate both objectives into one framework. In particular, this work proposes a framework for multi objective fitness functions within SHPO that balance model performance with carbon emissions. To this end, the SHPO framework uniquely integrates carbon tracking within the process of hyperparameter tuning to make sustainability. Additionally, it demonstrates the importance of systematically ranking the optimization techniques based on their environmental impact.

3. Methodology

The proposed work develops a framework called Sustainable Hyperparameter Optimization (SHPO) that incorporates multi objective fitness to optimize ensemble classification models like Random Forest, ExtraTrees, XGBoost, and AdaBoost. Figure 1 shows the work flow of proposed framework. The objective of the framework is to maximize the model accuracy and at the same time reduce carbon emission as part of the more significant cause of Green in ML. The framework uses both traditional and advanced optimization techniques, including Optuna, Hyperopt, and Grid Search. Each optimization procedure measures the power consumed using the package code carbon, besides the time duration of the hyperparameter tuning at the training stage of each model. Finally, the SHPO framework will use the TOPSIS as an MCDM method to identify the most sustainable hyperparameter configurations taking into account multiple objective fitness. multiple objective fitness simultaneously by focusing on the maximum predictive accuracy while minimizing the carbon emissions associated with training the models. After identifying the highest ranked set of hyperparameters, the framework fits the model with those parameters and applies that to test data. Experimental results obtained from the SHPO framework show which optimization technique performs the best, hence striking a good balance between accuracy and carbon emissions. It is also a significant step toward greener AI since the environmental impacts were embedded in this work while doing hyperparameter optimization.

3.1. Hyperparameter Tuning Techniques

The selection of hyperparameters is important in any machine learning model performance. Selection of optimal hyperparameter ensures the model achieve high accuracy. Proper tuning presence the model being overfitting or under fitting [19]. For that reason, the step of hyperparameter tuning is very crucial while developing ensemble classification model. There are three different hyperparameter optimization techniques in the work.

- Optuna: A very efficient and flexible optimization technique that uses a tree-structured Parzen estimator [TPE] for sequential model-based optimization. Optuna is designed to minimize computational overhead by dynamically constructing the search space.

- Hyperopt: A package for optimization with Bayesian optimization using TPE to find the best hyperparameters. Hyperopt will fit well for high-dimensionality optimization.
- Grid Search: Traditional approach that performs an exhaustive search over the predefined hyperparameter grid. Though computationally expensive, Grid Search is exhaustive in its search over the pre-defined hyperparameter space.

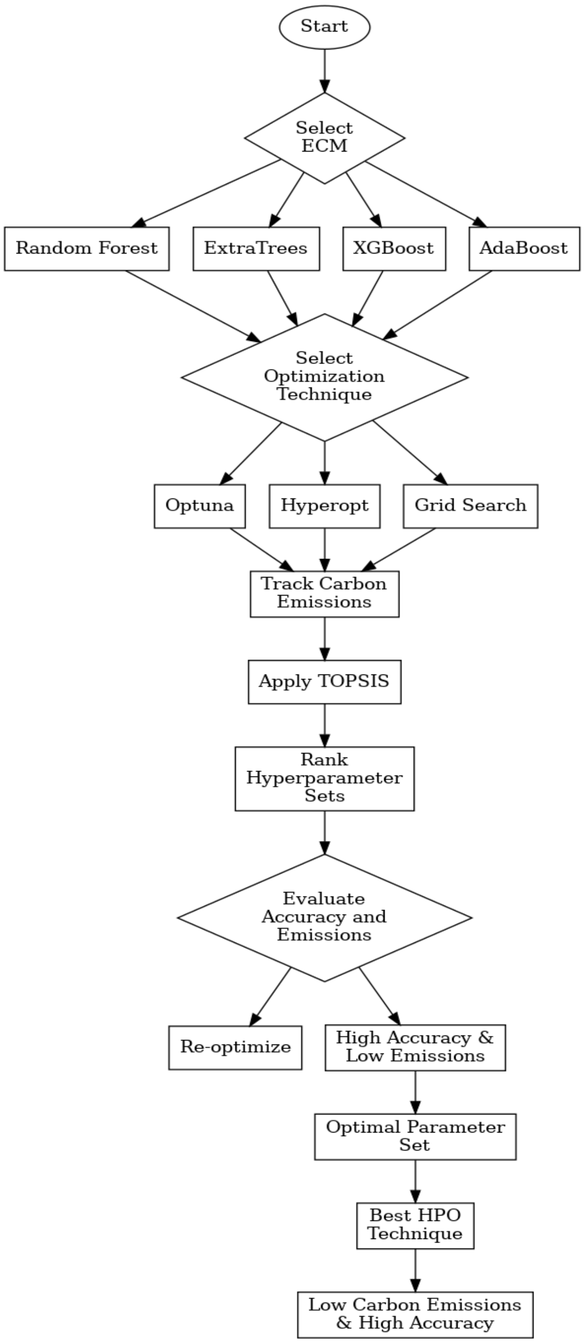

Fig.1. Sustainable hyperparameter optimization (SHPO) framework

3.2. Tracking Carbon Emission

Carbon emissions were tracked in the process of hyperparameter optimization to support Green AI's goals. This can be estimated by considering the power consumption of the CPU and the duration of computational tasks in order to calculate the carbon emission in kg CO2eq for each of the various optimization processes [20]. In this way, could quantify the environmental impact of every different hyperparameter configuration and make a comparison not only on accuracy but also on sustainability. The CodeCarbon package is used to measure the power consumption and time duration of hyperparameter tuning at the training stage. Codecarbon is initialized before the training process to monitor the energy consumption and calculate carbon emission itself. The tracker is started then the hyperparameter optimization runs the model training process for various parameter configurations. Once the optimization process complete codecarbon recodes the time taken for the process, total energy consumption in kWh with respect to time, calculate the carbon emission in kgCO_2 eq with respect to energy consumption. Finally, emission data stored in log file. The formula to estimate energy consumption and carbon emission as below.

$$Energy\ (Wh) = Power\ Rating\ (Watts) \times Time\ (hours) \tag{1}$$

Power Rating (W) refers to the power consumption of the hardware used for training the model.

$$C(X) = E(X)\ X\ Emission\ Factor \tag{2}$$

Where $E(X)$ represents the energy consumption associated with hyperparameter tunning for hyperparameter vector X. Emission Factor is the amount of CO_2 emitted per kWh of energy consumed. emission factor for electricity is 0.4 kg CO_2 per kWh.

3.3. Multicriteria Decision-making (MCDM) with TOPSIS

To determine the most sustainable hyperparameter settings of ECMs uses the TOPSIS a popular MCDM method. TOPSIS is particularly well suited for the situations where multiple conflict objectives such as maximizing accuracy and minimizing carbon emission. TOPSIS enabling fair normalize these criteria. TOPSIS ranks the alternative hyperparameter configurations by calculating their relative closeness to an ideal solution, which simultaneously maximizes accuracy and minimizes carbon emissions.

Normalization of decision matrix

$$\text{Accuracy } a_i = \frac{a_i}{\sum_{i=1}^{n} a_i^2} \tag{3}$$

$$\text{Carbon emission } c_i = \frac{c_i}{\sum_{i=1}^{n} c_i^2} \tag{4}$$

Ideal (I) and Negative-Ideal (NI) Solutions

$$\text{I Solution } S^+ = (\max(a), \min(c)) \tag{5}$$

$$\text{NI Solution } S^- = (\min(a), \max(c)) \tag{6}$$

Euclidean Distance

$$\text{Distance to the I solution } d_i^+ = \sqrt{(a_i - a^+)^2 + (c_i - c^+)^2} \tag{7}$$

$$\text{Distance to the NI solution } d_i^- = \sqrt{(a_i - a^-)^2 + (c_i - c^-)^2} \tag{8}$$

Relative Closeness (RC) to I Solution

$$\text{RC } C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{9}$$

The configuration with the highest C_i is the most balanced between accuracy and carbon emissions. Pseudocode presents the workflow of the SHPO framework.

Pseudocode of Sustainable Hyperparameter Optimization (SHPO) framework

Input: Dataset D, Ensemble Classification Models =\{RandomForest, ExtraTrees, XGBoost, AdaBoost,
Hyperparameter Search Spaces $\mathcal{H}$ for each model,
Optimization Techniques $\mathcal{O}$ = {Optuna, Hyperopt, Grid Search},
Carbon emission tracking CodeCarbon, evaluation function Accuracy.
Output: Optimal hyperparameter configuration θ^* for each model that balances high accuracy and low carbon emissions using TOPSIS. Suggest the best optimization Technique.

```
Initialize result R = []
For each model M in Models (M ∈ 𝓜):
   For each optimization technique O in Optimization Techniques (O ∈ 𝓞):
      For each hyperparameter configuration θ in Hyperparameter Search Space H (θ ∈ 𝓗):
            accuracy = Accuracy(M, θ, D)
```

carbon_emission = CarbonEmission(M, θ, D)
R.append((M, O, θ, accuracy, carbon_emission))
End
End
End
Apply TOPSIS to rank all configurations in R for model M:
Create decision matrix D for model M:
Rows: Each hyperparameter configuration θ
Columns: Accuracy and Carbon Emissions
Normalize the decision matrix D:
For accuracy (higher is better) in equation 3
For carbon emissions (lower is better) in equation 4
Determine the I and NI solutions:
I solution in equation 5
NI solution in equation 6
Calculate the Euclidean distance from each configuration to the I and NI solutions:
Distance to I solution in equation 7
Distance to NI solution in equation 8
Calculate the RC to the I solution for each configuration in equation 9
Rank the configurations based on values.
Select the top-ranked configuration as the optimal hyperparameters θ for model M.
Return the optimal hyperparameter configurations θ for all models M in $\mathcal{M}$.
Fit all models M in $\mathcal{M}$ using the corresponding hyperparameter configurations θ and test the framework using test data.
Finally suggest the best optimization technique with consideration of objective.

4. Result and Discussion

The experimental evaluation was performed on the Breast Cancer dataset available in the Kaggle repository. It is among the most popular binary classification datasets, containing 569 samples, each described by 30 features. The features are representing different measures of the cell nuclei: radius, texture, perimeter, area, smoothness, and more. The dataset is balanced, with 212 samples labeled as malignant and 357 as benign; therefore, it is the ideal candidate to evaluate the performance of the ECMs. The different ECMs used in the experiment are Random Forest, ExtraTrees, XGBoost, and AdaBoost. For each model, hyperparameter optimization was considered through three tradition and advanced optimization techniques such as Optuna, Hyperopt, and Grid Search. Their tuning included a range of their own hyperparameters, which are listed below in Table 1.

Table 1. hyperparameter workspace

Model	Parameter	Values
RandomForest	No of estimators	[50,100,150 200]
	Maximum depth	[10, 20,30]
ExtraTrees	No of estimators	[50,100,150 200]
	Maximum depth	[10, 20,30]
XGBoost	No of estimators	[50,100,150 200]
	Maximum depth	[3, 6,12,15]
	learning-rate	[0.01, 0.08,0.1]
AdaBoost	No of estimators	[50,100,150 200]
	Learning rate	[0.01, 0.08,0.1]

The SHPO was aimed to find the best hyperparameter combinations that satisfy the multi objective fitness approach. This approach is to maximize model accuracy while minimizing the carbon emissions. The best hyperparameter combination obtained by the multi-objective fitness approach for each ECMs, and the accuracy and carbon emissions associated with it for each of the hyperparameter optimization techniques are summarized in Table 2. Carbon emission is measured in the form of kg CO2eq. Equation 10 denoted the accuracy formula.

$$Accuracy = \frac{No\ of\ Correct\ Predictions}{Total\ no\ of\ Predictions}\ X\ 100 \tag{10}$$

Table 2. Best Parameters corresponding accuracy and carbon emissions for Various ECMs

ECMs	Optimization Method	Best Parameters	Best Accuracy	Carbon Emissions (kg CO2eq)
Random Forest	Optuna	{ No of estimators: 100, Maximum depth: 15}	**0.97**	**3.51E-04**
	Hyperopt	{Maximum depth: 8, No of estimators: 69}	0.96	7.35E-04
	Grid Search	{Maximum depth: 10, No of estimators: 200}	0.96	2.97E-05
Extra Trees	Optuna	{No of estimators: 165, Maximum depth: 16}	**0.969**	**9.29E-04**
	Hyperopt	{Maximum depth: 5, No of estimators: 60}	0.969	1.13E-03
	Grid Search	{Maximum depth: 20, No of estimators: 200}	0.962	5.14E-05
XGBoost	Optuna	{No of estimators:158, Maximum depth: 4, 'learning rate': 0.0353}	0.967	1.46E-03
	Hyperopt	{'learning rate': 0.0606, Maximum depth: 0, No of estimators: 93}	0.967	1.68E-03
	Gridsearch	{'learning rate': 0.1, Maximum depth: 3, No of estimators: 200}	**0.969**	**8.40E-05**
AdaBoost	Optuna	{No of estimators: 90, 'learning rate': 0.0999}	**0.971**	**2.05E-03**
	Hyperopt	{'learning rate': 0.08292, No of estimators: 46}	0.971	2.39E-03
	Grid Search	{'learning rate': 0.1, No of estimators: 100}	0.967	1.15E-04

Table 2 shows the optimal hyperparameter settings of various ECMs. These settings have been identified based on three different optimization methods. In the table, within each model, the best set of performing hyperparameters is identified using the TOPSIS method based on the corresponding accuracy and carbon emissions. In Table 3, the best optimization techniques of the various ECMs are shown. This table presents the best hyperparameter settings of each optimization technique, the corresponding accuracy and the associated carbon emissions for each model.

Table 3. Best optimization technique of ECMS using MCDM

Model	Optimization Technique	Best Parameters	Best Accuracy	Carbon Emissions
Random Forest	Optuna	{No of estimators: 100, Maximum depth: 15}	0.97	3.51E-04
Extra Trees	Optuna	{No of estimators: 165, Maximum depth: 16}	0.969	9.29E-04
XGBoost	Grid search	{'learning rate': 0.1, Maximum depth:3, No of estimators: 200}	0.969	8.40E-05
AdaBoost	Optuna	{No of estimators:90, 'learning rate': 0.0999}	0.971	2.05E-03

The results indicate that Optuna is generally more effective at balancing accuracy and carbon emissions across most models. therefore, it may be a promising tool toward sustainable hyperparameter optimization. More precisely, Optuna provided lower carbon emissions without compromising the accuracy, especially for the Random Forest and ExtraTrees models. Grid Search, while resulting in higher accuracy in some other cases, also provides higher carbon emissions.

5. Conclusions

This paper introduced a new sustainable hyperparameter optimization (SHPO) framework. This framework uses a multi objective fitness technique to balance high accuracy and low carbon emissions. It achieves the multi objective fitness with the help of TOPSIS when tuning ensemble classification models (ECMs), which is the multicriteria decision-making (MCDM) method. The SHPO framework was tested on a breast cancer dataset. Optuna constantly resulted in the lowest carbon emissions with high accuracy among other techniques compared, Hyperopt and Grid Search. For the Random Forest model, Optuna achieved an accuracy of 0.97 and a carbon emission of 3.51E-04 kg CO2eq. Grid Search, even though achieving the same accuracy of 0.963, had a lower carbon emission of 2.97E-05 kg CO2eq. Similarly, Optuna reached an accuracy of 0.971 and carbon emissions of 2.05E-03 kg CO2eq for Adaboost, showing that it effectively balances these important factors.

These findings raise awareness to consider the environmental impact of developing the ML models, especially for more complex datasets requiring more computational resources. By adopting Green AI practices, like the algorithmic optimization approach presented in this paper. The future of this work can contribute towards both software and hardware optimization for more sustainable and environmentally friendly AI technologies. This study provides a way for future research in Responsible AI by showing the importance of focusing on performance and sustainability.

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